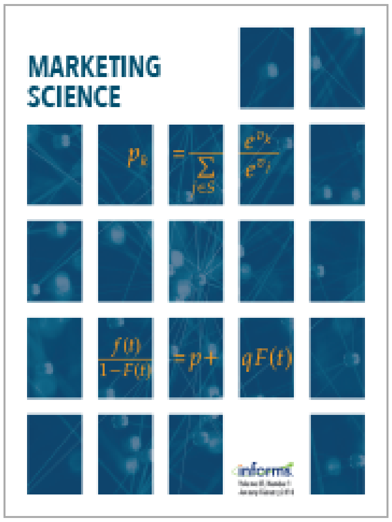

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GMO and Non-GMO Labeling Effects: Evidence from a Quasi-Natural Experiment

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Abstract. The United States recently mandated disclosure labels on all foods that contain genetically modified organisms (GMOs), despite longstanding, widespread use of voluntary third-party non-GMO labeling. We leverage the earlier passage and implementation of a mandatory GMO labeling law in Vermont as a quasi-natural experiment to show that adding this mandatory labeling into a market with pre-existing voluntary non-GMO labels had no effect on demand. Instead, the legislative process made consumers aware of GMO topics and increased non-GMO product sales before the GMO labeling mandate went into effect. The GMO-related legislative processes also increased non-GMO product demand in other states that considered, but did not implement, GMO labeling mandates. We find that 36% of new non-GMO product adoption can be explained by differences in consumer awareness tied to legislative activity. Our findings suggest that voluntary non-GMO labels may have provided an efficient disclosure mechanism without mandatory GMO labels.

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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 U.S. adults believe that foods containing GMO ingredients are less healthy than foods without them; 88% of consumers have strong preferences for labeling this credence attribute (Annenberg Public Policy Center 2016).[2] Nonetheless, 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. Public policy initiatives such as mandatory disclosure of ingredient types can impact consumer behavior *directly* through its implementation and *indirectly* through another mechanism: The legislative process itself can raise 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 awareness effect dominates. That is, we find that legislative activity heightened consumer awareness about GMO topics and increased the adoption of products with voluntary non-GMO labels, even without the actual implementation of mandatory GMO labeling. We also show that implementation of mandatory GMO labeling in Vermont had no additional direct effect on demand for GMO or non-GMO products.

It is often difficult to decompose the direct and indirect effects of a policy initiative, but we can do so by leveraging the institutional context. We carefully delineate the time period when only voluntary non-GMO labels existed (i.e., no mandatory GMO labels existed), as well as the period when both labels existed concurrently.

Our empirical setting is the ready-to-eat (RTE) cereal market, which comprises a significant share 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 market sales data with a novel data set 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 United States.

Our empirical analysis proceeds in three main parts. First, to establish the indirect awareness effect in a broad context, we examine the relationship between the adoption rate of newly introduced non-GMO products and consumers' awareness of GMO-related topics at the time of product introduction. We construct a measure of the information environment—proxied by location-specific Google Trends Search Volume Indices (Google SVI)—to assess varying levels of consumer awareness around GMO issues. Fifty-five distinct products carrying voluntary non-GMO labels were introduced in 9,590 grocery stores across the United States during our sample period. We show that the heterogeneity in the adoption of these products across different locations was predicted by consumer interest in GMO topics at the time of entry in those locations. This adoption rate was the highest during the time periods coinciding with GMO legislative activity in the seven states that had mandatory GMO labeling initiatives. In fact, we find that about 36% of the new non-GMO product adoption rate can be explained by the information environment differences tied to legislative activity. In multiple robustness and placebo tests we show that this relationship cannot be explained by differential pricing, product entry, or other plausible confounders. Overall, we show that legislative activity itself, by raising consumer awareness about GMO topics, led to increased adoption of non-GMO products without any mandatory GMO labeling laws actually being implemented.

Second, we focus on Vermont, the only state to pass and fully implement a GMO labeling law. We use this quasi-natural experiment to understand the relationship between non-GMO product demand and the information environment specifically tied to the passage and implementation process of the law prior to labels appearing on products. As Vermont began the process of implementing the law, its consumers experienced a unique information environment that increased their exposure to discussions around GMO topics. Notably, the information environment in Vermont significantly diverged from the neighboring state, Maine, which also passed a GMO labeling law around the same time but failed to implement it due to a conditional trigger clause. Accordingly, our information measure shows initial similarity and subsequent divergence in the information environment between Vermont and Maine. We use the synthetic control 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 passage of the law. We show that the consumption of non-GMO products increased more in Vermont than in Synthetic Vermont after the unconditional passage of its mandatory GMO labeling bill. The unique setting in Vermont also allows us to better understand the source of information responsible for the increase in non-GMO demand in Vermont: We study differential demand patterns within Vermont's designated market areas (DMAs) that also cover neighboring states and find evidence consistent with the effect stemming from Vermont-specific on-the-ground information efforts rather than traditional media.

Last, having shown an economically meaningful indirect effect of GMO legislative activity in both broader and Vermont-specific settings, we formally explore its direct effect. We analyze whether any additional demand changes occurred in Vermont after products began carrying mandatory GMO labels and find no statistically discernible impact on demand in Vermont. 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 the understanding of how public policy initiatives facilitate consumer choice. An extensive empirical literature has examined the effect of policy-mandated information disclosure on market outcomes, for example, 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, Rao and Wang 2017, Bollinger et al. 2022). Our study examines the role of the information environment generated by policy activity in shifting consumer demand even without policy implementation, similar to Taylor et al. (2019) in the context of soda taxes.

Our results sharply contrast with those from previous studies that suggest GMO labeling itself has a large direct negative effect on demand. 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 and Dannenberg et al. 2009). The vast majority of these prior studies rely on stated preference (survey) or laboratory experiment data rather than actual market transactions and, thus, fail to capture the complexity of alternative information signals that exist in the marketplace. 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 may diverge substantially from perceived consumer attitudes (Sunstein 2020). Our analysis uses actual retail-level consumer purchase data to circumvent issues with stated preferences or hypothetical scenarios and accounts for several complex mechanisms above and beyond GMO labeling that shape consumer demand response in differentiated product markets.

Nevertheless, as the food industry navigates the details of a national mandatory labeling standard for GMO foods in the United States, 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, Barahona et al. 2020, Alé-Chilet and Moshary 2022). 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.

2. Background and Institutional Setting

Our empirical analysis uses the timing of mandatory GMO labeling initiatives across several U.S. states, with a particular focus on the quasi-natural experiment in Vermont. In this section, we provide key institutional details on state-level GMO labeling initiatives and Vermont-specific lawmaking activities that are relevant for our analysis.[3]

2.1. State-Level Mandatory GMO Labeling Initiatives

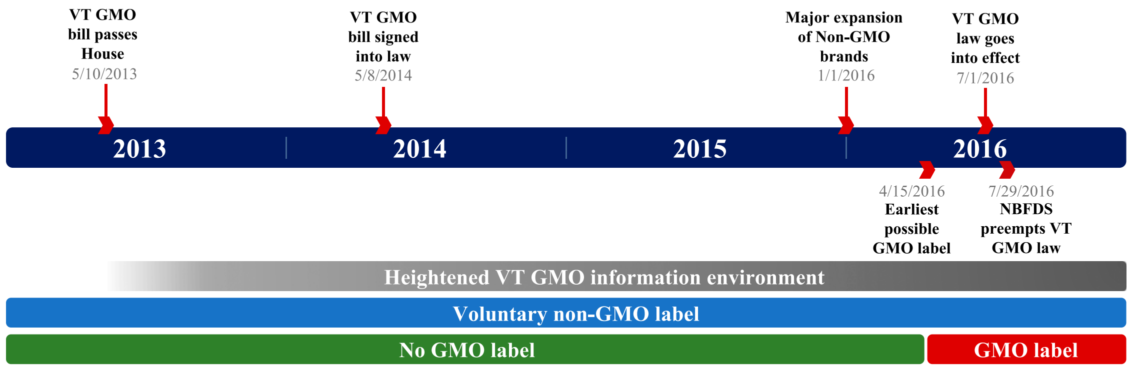
In the last decade, a patchwork of state-level legislation in several states has been proposed on mandatory GMO labeling, with the public debate becoming considerably more mainstream around California's Proposition 37 in 2012 (Bovay and Alston 2016). Besides California, in 2013 and 2014, major legislative activity on GMO labeling also emerged in Connecticut, Maine, Vermont, Washington, Colorado, and Oregon. Vermont passed a mandatory GMO labeling bill in its state House in May 2013. A month later both Maine and Connecticut passed mandatory GMO labeling laws; however, both these laws contained trigger provisions that were never met, and the laws were therefore never implemented. In November 2013, Washington state narrowly voted down a ballot measure for mandatory GMO labeling, followed by similar defeats of GMO labeling ballot initiatives in November 2014 in Oregon and Colorado.

The labeling law activity in each state resulted in a temporary heightening of consumer awareness surrounding GMO topics, as measured by Google SVI. Moreover, these changes to the information environment happened irrespective of whether the bill passed or not, suggesting that the policy process itself affected the information environment more so than the bill's final outcome.

2.2. Vermont GMO Labeling Law and Timeline

Vermont was the first and only state to successfully pass and implement a mandatory GMO labeling law. The bill was passed by the House in May 2013 and unconditionally signed into law by the governor in May 2014 with a slated implementation date of July 1, 2016. The law required food manufacturers to label products sold in Vermont with a GMO label if they contained greater than 0.9% GMO ingredients by weight.

Figure 1. (Color online) Vermont GMO Legislation Timeline



After the law was passed, the rule-making process began, garnering significant local attention and increased consumer exposure to discussions around anti-GMO topics 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 anti-GMO grassroots initiatives. During this time, several failed attempts were made at the federal level to preempt the Vermont law; and in March 2016, about three months prior to implementation of the Vermont law, numerous national food brands (General Mills, Kellogg's, Mars, ConAgra Foods, and PepsiCo) unexpectedly announced that they would begin *nationwide* GMO labeling in response to Vermont's *state*-level labeling law (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. The companies that chose to comply with Vermont law in this way did not widely publicize the labels, possibly to mitigate any expected negative consumer response.

Just 28 days after Vermont's law went into effect, President Obama signed into law the National Bioengineered Food Disclosure Standard (NBFDS) on July 29, 2016, establishing a national mandatory GMO labeling standard. While companies had until January 1, 2022, to comply with labeling requirements, the law immediately preempted all state-level labeling, thereby overturning the Vermont law upon passing (for more information on NBFDS, see Bovay and Alston 2018). Figure 1 visually summarizes the timeline of key events that occurred during the period surrounding Vermont's passage of GMO legislation.

3. Data Description and Analysis Roadmap

3.1. Data and Descriptive Statistics

3.1.1. Sales Data. Our primary data source is the Nielsen Retail Scanner (RMS) data provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business. Our sample focuses on the RTE cereal market and spans five years, from 2012 to 2017, a period that includes implementation of the Vermont mandatory GMO labeling law in July 2016. The RMS data records weekly quantities sold, revenue, and product information for items sold in 10,456 grocery stores across the 48 contiguous US states. Product information includes universal product code (UPC), product name, corporate name, package size (in ounces), and flavor variant.[4] We use these data to calculate the 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. As a result, our baseline data set contains quantity and price information for products sold in month t at store s between January 2012 and December 2017.

3.1.2. 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 data set 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. Figure 2 presents an example of the typical non-GMO (NGPV) label. The NGPV standard is the leading third-party verification program for GMO avoidance in North America, with more than 60,000 verified products.

Figure 2. (Color online) Non-GMO Project Verified Label

These NGPV data include UPC-level information and the date when each product was certified.[5] We summarize quantity share, prices, quantity, and number of products for all non-GMO products in our sample in Table 1A, separately for the seven states that experienced legislative activity and for all other contiguous U.S. states. As is clear from Table 1, although prices are comparable between the two sets of states, those with legislative activity have larger non-GMO product assortments and overall non-GMO quantities sold and share of quantities sold on average.

3.1.3. 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 products and parent companies for which we have such verifiable information. To analyze the effect of mandatory GMO labeling, we therefore focus on the three largest parent companies in the RTE cereal category—General Mills, Kellogg's, and Post (Big 3)—whose combined market share accounts for around 83% of the national market for RTE cereal. 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 RTE cereal products under the umbrella of the Big 3 companies by reviewing official company announcements and press releases made in 2016. 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.

Table 1B summarizes the quantity share, prices, quantity, and number of products for GMO products of Big 3 companies in our sample, separately for the seven states with legislative activity and for all other contiguous U.S. states. Prices in the two sets of states are similar, much like in Table 1A; however, quantity patterns differ between state groupings for Big 3 GMO products. States with legislative activity have lower average GMO product consumption, but at the same time carry a greater assortment of GMO brands. We use these data in Section 5 to examine the direct effects of GMO labeling in Vermont.[6]

3.1.4. Non-GMO Product Entry Data.

We define new product introduction at the store level based on whether a particular store sold a given product up to that point in time. We observe 55 different non-GMO (NPGV) product introductions in 9,590 grocery stores across different locations in the United States.[7] Our new entrants' sample spans the time period from January 2013 through June 2016. 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 before the implementation of mandatory GMO labeling in Vermont (July 2016). For each new product entry, we look at the initial adoption rate of that product, as measured by its average quantity share over the first six months after entry in a given store.

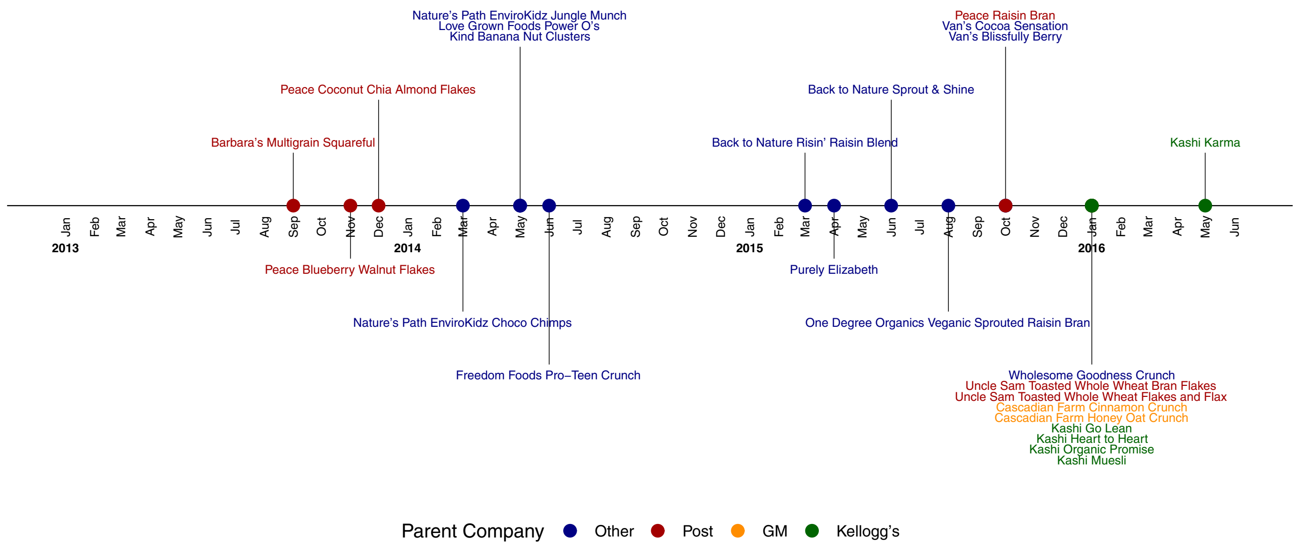
Figure 3 illustrates the entry timeline of the top 25 largest non-GMO brand introductions (out of 55 total)

Table 1. Summary Statistics of Non-GMO and GMO Products (Big 3)

	Panel A: All non-GMO products				Panel B: Big 3 GMO products			
	Seven states		Other states		Seven states		Other states	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Quantity share	0.039	0.022	0.021	0.014	0.816	0.066	0.851	0.072
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
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 shares are overall quantity sold of all non-GMO or GMO products of a store divided by the category quantity sold in that store. Price is in dollars per ounce. Quantity is weighted average quantity of RTE cereal sold in 10,000 ounces averaged across months and stores.

Figure 3. (Color online) Timeline of Top-25 Largest Non-GMO Product Introductions



by sales revenue in the United States between 2013 and 2016. In this figure, the indicated entry timing corresponds to the first observation of a given brand across all stores in our sample. The same brand typically entered different stores in our sample (even within the same state) at different times, and we exploit this differential entry timing in our identification strategy outlined below. Although 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. 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 the 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. Online Appendix A.2 provides details about the revitalization of Kashi product lines that led to this product expansion.

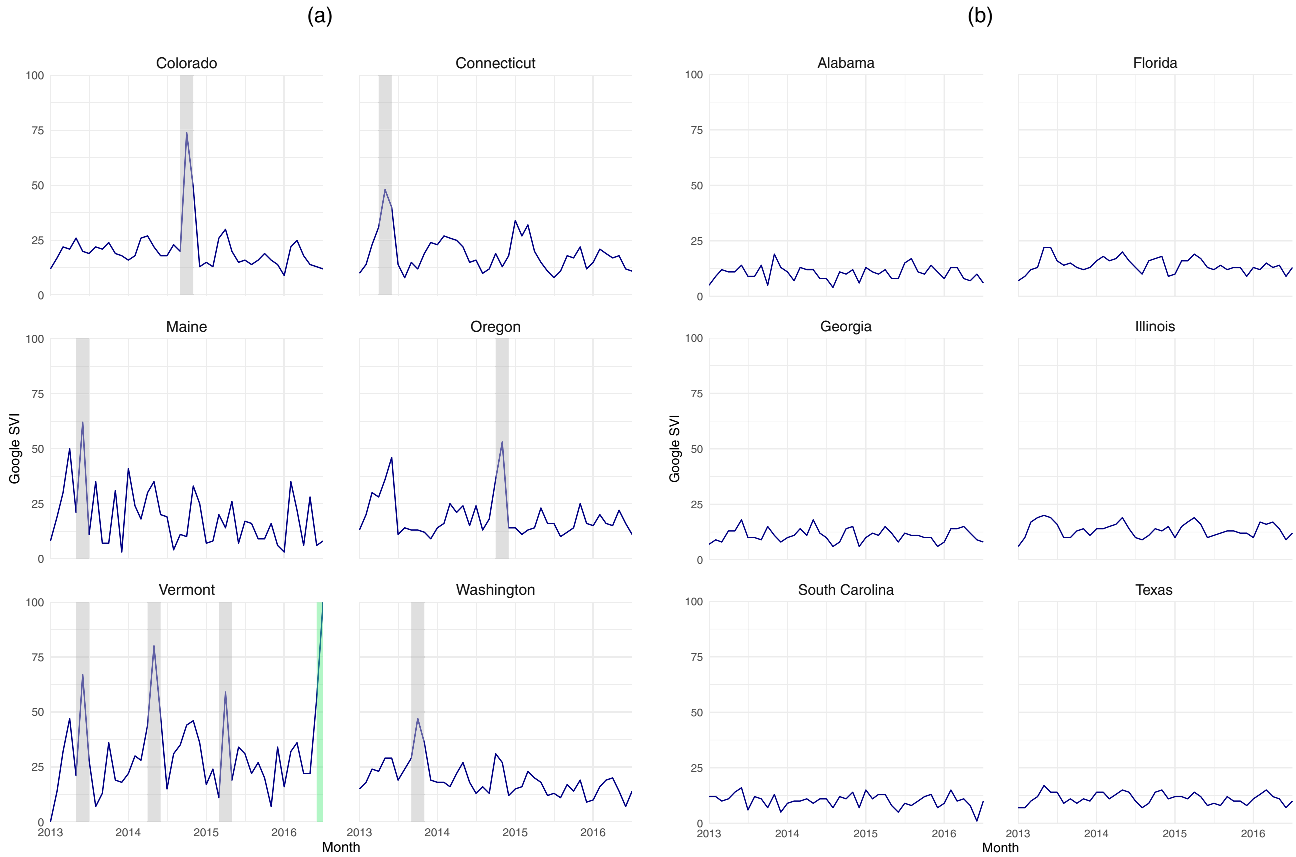
Table 2A reports initial adoption rates (quantity shares) and prices for all 55 non-GMO product introductions for all contiguous U.S. states, for the seven states with GMO legislative activity, and for all contiguous U.S. states excluding those seven states. Across the United States, the average initial adoption rate for newly entering non-GMO products—the monthly quantity share averaged across all new products over six months after entry—was 0.370%. In the seven states with legislative activity, however, the adoption rate was notably higher (0.452%). Meanwhile, prices were quite similar (around $0.33 per ounce) across all three groups.

3.1.5. Google Search Volume Index Data. In the absence of detailed data on evolving consumer interests in GMO topics across states, we use Google Trends as a proxy for varying levels of consumer interest in and awareness of GMO-related topics across states and time, as captured by online searches.

To identify the most relevant keyword(s) for this analysis, we use the search engine optimization tool suite SEMrush. We opt to document Google Trends for the most common search term that is searched among all non-GMO and GMO related keywords—"GMO." 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 web page on "What is a GMO?"; and (3) the currently archived *Nature* web page on the use of GMO technology. Based on the related safety-focused search terms and analysis of the information content of these websites, we infer that the Google SVI data primarily capture the increased consumer concern and awareness of anti-GMO sentiment rather than the scientific consensus on the safety of GMOs. We construct a panel of Google SVI for 48 states for every month spanning the period between January 2012 and December 2017, making the monthly measures 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

Figure 4. (Color online) Google Trends Search Volume Index for States with and without GMO Labeling Law Activity



Notes. (a) States with GMO labeling law activity. (b) Sample of states without GMO labeling law activity. The shaded vertical bars in (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 passing votes in the state House (05/10/2013) and Senate (05/08/2014), and the failure of the GMA federal injunction attempt (04/27/2015); the final shaded vertical bar coincides with the implementation of mandatory GMO labeling (07/01/2016).

and July 2016. Figure 4(a) shows the six states with significant GMO labeling law activities.[8] The gray vertical bars highlight the time periods when important 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. The highlighted areas for Connecticut, Maine, Oregon, and Washington are similarly defined. In Vermont, the highlighted areas reflect several important developments, in chronological order: (i) passage of the GMO labeling bill in the House; (ii) passage of the bill in the Senate and being signed into law; (iii) rejection of a major federal lawsuit, which was the only credible threat to implementation of the Vermont labeling law; and (iv) law implementation (highlighted in green). See Online Appendix A.1 for more details about this timeline. Figure 4(b) presents a parallel time series of Google SVIs for a sample of states without any such legislative activity.

Table 2B summarizes the average Google SVI for all contiguous U.S. states, for the seven states with GMO legislative activity, and for all other contiguous U.S. states. For each of the three state groupings, we also report the average Google SVI over the time periods that reflect the peak legislative periods in the seven states with legislative activity (corresponding to the gray shaded areas in Figure 4(a)) and over the remaining off-peak nonlegislative periods. The average SVI over the legislative periods for the seven states with GMO labeling law activities (SVI = 32.04) is nearly twice that of the nonlegislative periods in the same seven states (SVI = 17.11), and it is more than double the average SVI over the same peak legislative periods for all other states with no activity (SVI = 14.59).

Overall, Figure 4 and Table 2B illustrate 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 of GMO-related issues at a specific time and in a particular state.

We acknowledge that the cross-sectional variation in this measure may also capture pre-existing preferences

Table 2. Summary Statistics of Non-GMO Entrants and Google SVI

	Overall		Seven states		Other states	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Panel A: Newly introduced non-GMO products						
Quantity share (in %)	0.370	0.663	0.452	0.731	0.343	0.636
Price	0.331	0.136	0.333	0.121	0.331	0.14
Quantity	0.006	0.010	0.005	0.006	0.006	0.006
Panel B: Google trends search volume indices						
Average SVI	14.23	7.88	20.55	11.30	13.87	6.66
Legislative period SVI	15.71	8.36	32.04	17.36	14.59	6.90
Nonlegislative period SVI	13.12	6.48	17.11	8.06	12.44	5.91

Notes. Sample period is from January 2013 through June 2016. Seven states refers to California, Colorado, Connecticut, Maine, Oregon, Washington, and Vermont. Legislative period refers to all the time periods when the seven states' labeling law activities respectively took place. We show respective SVIs during those same time periods for other state groups as well. The products' statistics are averaged across all new products over six months after entry. Quantity shares are product-level quantity divided by the category quantity in that store multiplied by 100. Price is in dollars per ounce. Quantity is expressed in 10,000 ounces. Quantity shares, price, and quantity are weighted averages over the first six months after entry of a given product in a store.

independent of the information environment. Data limitations prevent us from fully disentangling the factors that drive changes in the Google SVI measure, and thus we are agnostic toward fully explaining the mechanism behind it. We do, however, provide consistent evidence in our analysis that the information environment tied to legislative activities is one of the important drivers of the variation in this measure.

3.2. Roadmap of Empirical Analysis

Broadly, our empirical analysis proceeds in three main parts, summarized in Table 3. The first two parts in Section 4 examine the *indirect* awareness effect of mandatory GMO labeling on non-GMO product demand and offer complementary insights based on two different settings. In both sets of analyses, we quantify this indirect information effect and find comparable estimates of the information elasticity of demand of about 0.5–0.6.

First, in Section 4.1, we use the variation in state-specific awareness around GMO topics in all US states to analyze the effect of information on the adoption rate of newly introduced non-GMO products. This analysis shows that legislative activity, even without passage or implementation of a law, leads to higher consumer awareness and non-GMO product adoption.

Second, in a complementary analysis in Section 4.2, we use the quasi-natural experiment in Vermont to examine the relationship between information specifically tied to the passage and implementation process of the law (prior to labels appearing on products) and overall non-GMO product demand. In this setting, we use the synthetic control method to isolate the information effect attributable to the passage and implementation process of a mandatory GMO labeling law. The case study of Vermont also allows us to better understand the source of information responsible for the diverging non-GMO demand patterns in Vermont. We find evidence that the effect is attributable to on-the-ground information efforts rather than traditional media.

Last, the third part in Section 5 focuses on the *direct* effects of mandatory GMO labeling. We use the implementation of the Vermont mandatory GMO labeling law—when products began carrying the GMO label—to explore this relationship. In this analysis, we estimate the effect of the mandatory GMO label itself on both GMO and non-GMO product demand and find a null result.

The three sets of analyses each leverage different aspects of the institutional contexts of GMO and non-GMO labeling, different timelines, and different estimation approaches that offer the most appropriate identification strategies given the data limitations in each setting.

Table 3. Roadmap of Empirical Analysis

GMO labeling effects	Geography	Data sample	Scope
4. Indirect awareness effect	4.1. Entire United States 4.2. Vermont	New non-GMO product entry All non-GMO products	Information effect on non-GMO demand (information elasticity)
5. Direct label effect	Vermont	All GMO and non-GMO products	GMO label effect on GMO and non-GMO demand

4. Indirect Effects of Mandatory GMO Labeling Policy

In this section, we explore consumers' awareness of and the information environment surrounding GMO topics and their relationship to demand for voluntarily-labeled non-GMO products in two different settings. The first setting establishes this relationship for newly entering non-GMO products across the United States irrespective of the final outcome of legislation; the second setting isolates the effect attributable to the passage and implementation process (but before labels arrived on store shelves) of a mandatory GMO labeling law in Vermont.

4.1. Information Environment Across the United States

First, we examine the short-term adoption rate of newly introduced non-GMO products across the United States. We analyze this pattern using 55 distinct non-GMO product introductions in grocery stores across the United States and demonstrate that the variation in the information environment—proxied by Google SVI—predicts the adoption of these products in the period shortly after their entry. As shown in Figure 4, part of the variation in the information environment is driven by legislative activities, even without the implementation of a GMO labeling law.

4.1.1. Empirical Specification. Our research design exploits variation in the local GMO information environment and variation in introductions of non-GMO products across locations and time. We relate average quantity shares of newly introduced non-GMO products to average state-level Google SVIs during a short time frame after product entry. We do this by first constructing a product-store-month panel and linking the monthly Google SVI measure to each newly introduced product's quantity share. The panel contains the quantity share and the Google SVI for each newly entering product i at store s (in state l) during month t. Because state-specific Google SVIs are highly volatile at the monthly level, we then take averages of the quantity shares and the SVIs over the first six months after entry and collapse each product-store observation. This data construction procedure smooths out the noise in the month-to-month SVI measure while retaining sufficient signal for our analysis (Narita and Yin 2018). For a detailed description of the data construction process, please see Online Appendix B.1. The final sample contains the average quantity share and the average Google SVI measure for each entrant i at store s (in state l) that entered during the month t. We use this sample to estimate the following specification:

$$\overline{Y}_{ist} = \beta\overline{SVI}_{ist} + \gamma_i + \phi_s + \lambda_{q_t} + \varepsilon_{ist}, \qquad (1)$$

where the dependent variable $\overline{Y}_{ist}$ is the quantity share (in percentage terms) of product i, entering store s in month t, averaged over the first six months after entry ($\overline{Y}_{ist} = 1/6\sum_{\tau=t}^{t+5} Y_{is\tau}$). Corresponding to the same time interval, $\overline{SVI}_{ist}$ is the average Google SVI in the state where store s is located and product i entered ($\overline{SVI}_{ist} = 1/6\sum_{\tau=t}^{t+5} SVI_{is\tau}$). Because SVI varies at the state, rather than store level, s and t determine $\overline{SVI}$ for a product-store combination. As such, two products that entered the same store at different times would have two different $\overline{SVI}$ measurements. Similarly, the same product that entered two stores at two different times within the same state would also have two different $\overline{SVI}$ measurements. The specification in Equation (1) also controls for product (γ_i), store (ϕ_s), and entry quarter (λ_{q_t}) fixed effects. Therefore, the coefficient of interest, β, captures how the market share incrementally changes with average Google SVI in the period immediately following product entry, above and beyond any systematic differences in adoption rates across stores and brands, after controlling for seasonality and overall time trends. We cluster the standard errors at store, brand, and entry quarter level (clustering at state and entry quarter level yields similar results and does not change result interpretation). Online Appendix B.1 illustrates the sample data structure and presents an alternative specification with monthly sales data that effectively yields the same results.

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, these non-GMO product entries happened both in states with substantial GMO labeling law activities, which lead to more intense information inflow and increased consumer awareness, and in states with no such activity. Because we include store fixed effects, which absorb cross-sectional variation in SVI among U.S. states, the identification of β relies on intertemporal variation in SVI within each state because of different entry timing of the same brand across stores in the same state. In Online Appendix Figure B1, we confirm that there is sufficient residual variation in the average SVI measure after controlling for store, brand, and time fixed effects. The identifying assumption is that the entry and pricing of the newly introduced products are not correlated with our measure of the information environment, which we confirm with a series of marketing mix stability tests presented in Online Appendix B.3.

4.1.2. Results The results of the baseline specification are presented in the first column of Table 4. We find that the local information environment plays both a

Table 4. Relationship Between Non-GMO Product Adoption and Google SVI

		Placebo tests	
	Baseline	Peak replacement	Time reversal
SVI	0.0157***	−0.00102	0.00627
	(0.00443)	(0.00199)	(0.00673)
Observations	25,457	25,457	25,457
R^2	0.723	0.722	0.722
Store fixed effects	Yes	Yes	Yes
Brand fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes

Notes. Clustered standard errors in parentheses. Peak replacement refers to a placebo test where the SVI peaks in the seven states with GMO labeling legislative activity (California, Colorado, Connecticut, Maine, Oregon, Washington, and Vermont) are replaced with the state-specific average SVIs outside those peaks. Time reversal refers to a placebo test where the contemporaneous average SVI is replaced with the future average SVI one year from an entry month.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

statistically significant and economically meaningful role in the adoption of newly entering non-GMO products.[9] To demonstrate the economic significance of this effect, Figure 5(a) plots the estimated baseline SVI effect, $\hat{\beta}\overline{SVI}_{ist}$, along with its 95% confidence interval, as a function of Google SVI. This figure clearly shows a positive relationship between Google SVI and the short-term quantity share of non-GMO product entrants. An increase of one standard deviation in SVI is associated with 0.053 (14.32%) increase in non-GMO adoption rate.

An intuitive way to interpret the economic magnitude of this point estimate is by calculating the *information elasticity of demand*, E_{SVI}: First, evaluated at the average level of entry quantity share, $Q = 0.37$, a one-unit increase in Google SVI corresponds to an increase in quantity share of $\beta = 0.0157$, which translates into a $\Delta\%Q = (0.0157/0.37) \times 100 = 4.24\%$ increase in quantity share. Second, evaluated at the average level of SVI = 14.2, a one-unit increase in Google SVI corresponds to a $\Delta\%\text{SVI} = (1/14.2) \times 100 = 7.04\%$ increase in the information environment measure. Therefore, $E_{SVI} = (\Delta\%Q)/(\Delta\%\text{SVI}) = 0.6$. In other words, a 10% increase in Google SVI predicts a 6% increase in non-GMO product adoption rate.

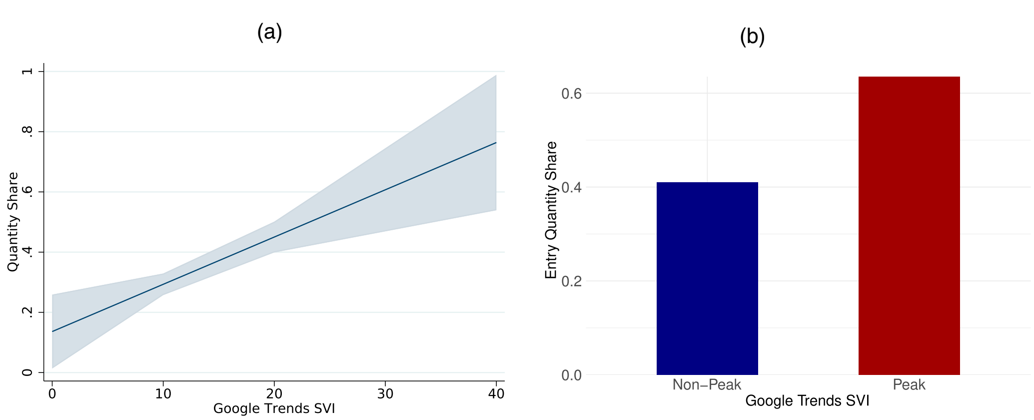
Another way to evaluate the economic magnitude of this information effect is to quantify the proportion of non-GMO product adoption rate that can be explained by the local information environment attributable to GMO labeling legislation activity. For this, we focus on the seven states with legislative activity and in Figure 5(b) compare the predicted non-GMO adoption outside peak legislative periods ($SVI^{non-peak} = 17.11$; $\hat{Q}^{non-peak} = 0.41\%$) with that during peak periods ($SVI^{peak} = 32.04$; $\hat{Q}^{peak} = 0.64\%$). We find that about 36% ($(0.64\% - 0.41\%)/0.64\% = 0.36$) of the new non-GMO product adoption within those seven states is attributable to the differences in the information environment tied to legislative activity.

4.1.3. Placebo Tests and Robustness.

We implement two placebo tests to ensure that our results are not driven by spurious residual correlation in the data. In designing the placebo tests, we identified scenarios where we do not expect to find a statistically significant Google SVI term.

In the first placebo test, we take the baseline specification data and replace the SVI of the peak periods in the seven states with GMO labeling legislative activity (highlighted in gray in Figure 4) with state-specific average SVIs outside those peak periods. The result, reported in the second column of Table 4, shows a null effect and suggests that the identifying

Figure 5. (Color online) Google Trends SVI and Quantity Share of the Non-GMO Product Entrants



Notes. (a) Estimated relationship. (b) Predicted entry shares (in %). (a) plots the estimated marginal Google SVI effect ($\hat{\beta}\overline{SVI}_{ist}$) reported in the first column of Table 4 with the corresponding 95% confidence interval. (b) focuses on the seven states with legislative activity and compares the predicted non-GMO product adoption outside peak legislative periods with non-GMO product adoption during peak periods. Non-peak SVI = 17.11; peak SVI = 32.04 (Table 2).

variation in our baseline specification is driven by surges in the information environment tied to state-level GMO legislation activity.

One might still be concerned about potential confounding factors that could drive both SVI and new product adoption simultaneously, even after controlling for store, brand, and quarter fixed effects. If such a confounder exists, then non-GMO product adoption would be correlated with both contemporaneous and future SVI. Our second placebo test assesses this possibility. In the time-reversal placebo test reported in the last column of Table 4, we replace the contemporaneous SVI averaged across the six-month period after entry month t with the future SVI averaged across the six-month period one year from the entry month, that is, $t+12$. As expected, we find a null effect for the future SVI. This suggests that the baseline results cannot be explained by any confound that affects both the information environment and non-GMO product consumption across geographic areas. Together, these two placebo tests demonstrate that our baseline specification appropriately captures the relevant signal and variation in the contemporaneous information environment from the Google Trends data.

Last, although our main result could be consistent with alternative explanations, such as lower non-GMO prices or more frequent introductions of non-GMO products in states and time periods with higher Google SVIs, we perform a set of marketing mix stability tests in Online Appendix B.3 and show that differential prices and assortment cannot explain differential short-term non-GMO product adoption. We also check the robustness of our results by including 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 Online Appendix B.5.

4.2. Information Environment in Vermont

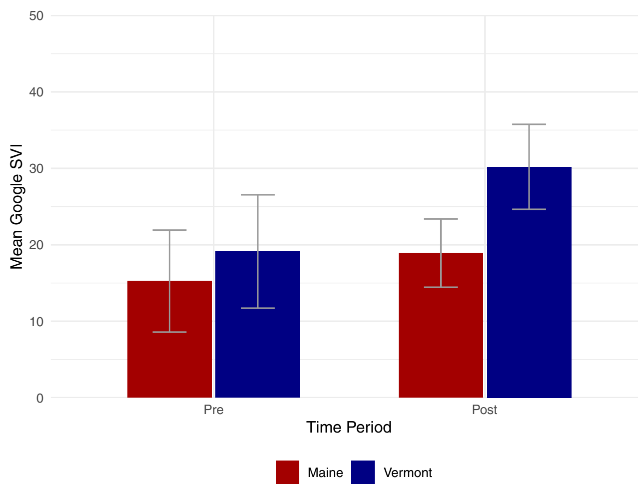
Next, we look at the demand for non-GMO products in Vermont, the only state to successfully pass and implement a mandatory GMO labeling law. Vermont experienced a localized influx of information that was specifically tied to the passage and implementation process of the law that other neighboring areas did not experience. We use this setting to isolate the impact of information attributable to the passage and implementation process of a mandatory GMO labeling law in Vermont on demand for non-GMO products before labels appeared on products. For this analysis, we expand our sample to include all non-GMO products—those previously existing and newly introduced—during our sample period. We also conduct a test using DMA border areas to better understand the source of the information divergence in Vermont after passage of the law, which we attribute to on-the-ground efforts tied to the law's implementation.

4.2.1. Institutional Context for Identification. A mandatory GMO labeling law was unconditionally passed and implemented in Vermont, whereas in Maine a labeling law was passed around the same time but never implemented. The major difference in the information environments between Vermont and Maine therefore stems from additional consumer awareness generated *after* the successful law passage in Vermont, primarily tied to the rule-making process associated with implementation. For details on the information campaigns and the rule-making process in Vermont, see Online Appendix A.1.

Both states' GMO labeling bills originated within weeks of each other, and prior to passage of the Vermont law, the information environments in Maine and Vermont were comparable. However, when the Vermont law passed the House 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. The similarity in information environments prior to the law passage and the subsequent divergence is also reflected in Google Trends data. Figure 6 illustrates that prior to May 2013, the difference in the monthly averages of Google SVI scores for Maine and Vermont was statistically indiscernible. In the period after, the monthly average SVI in Maine remained statistically unchanged, whereas that in Vermont diverged appreciably, resulting in a 64.5% higher mean Google SVI score in Vermont than Maine.[10] In the following analysis, we specify May 2013, the month when the Vermont mandatory GMO labeling law passed the state house, as the treatment month.[11]

4.2.2. Synthetic Vermont. Having established that Maine is an appropriate control, we implement the synthetic control (SC) method (Abadie et al. 2010, 2015) by looking for counties in Maine where consumption patterns are most similar to those in Vermont *prior* to the information environment divergence. The SC method constructs a "clone" of the treated unit (Vermont) by using a convex combination of different counties in Maine, hereafter referred to as Synthetic Vermont. The main outcome of interest is the quantity share of non-GMO products, so the measured treatment effect is the differential non-GMO quantity share between the two locations due to variation in consumer awareness and the information intensity around GMO topics. The preperiod spans January 2012 to April 2013 and the postperiod spans May 2013 to March 2016 (March 2016 is the latest month for which we can confirm that no GMO labels existed in Vermont).

Figure 6. (Color online) Maine vs. Vermont Mean Google SVI Scores Pre vs. Post



Notes. Treatment period begins in May 2013, the month when the Vermont mandatory GMO labeling law passed the state house. Pretreatment period is from January 2012 to April 2013. Post-treatment period is from May 2013 to March 2016. In the post period, the mean Vermont SVI score is 64.5% higher than the mean Maine SVI score. Error bars are 95% confidence intervals.

The SC method performs better with less volatile data, so 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, and these Maine counties constitute a donor pool of control units for the synthetic match procedure. Following Ferman and Pinto (2021), who show that a demeaned version of the SC method substantially improves efficiency and reduces bias, we demean the time trend variables by subtracting their pretreatment location-specific averages. This method improves matching quality considerably in our setting (root mean squared prediction error (RMSPE) is 0.0032 with demeaning and 0.0129 without demeaning). In constructing Synthetic Vermont, we use a number of predictive variables to capture preperiod non-GMO product consumption trends, prices, and assortments. We include three types of predictive variables: (i) pretreatment GMO and non-GMO consumption patterns; (ii) pretreatment trends in assortment (to ensure that the scope of new product introductions is similar); and (iii) pretreatment prices (to ensure that changes in demand in the postperiod are not attributable to divergence in prices). The complete list of the controls is listed in Online Appendix C.1. Resulting Synthetic Vermont is constructed as a weighted average of select Maine counties from the donor pool that minimizes RMSPE. Online Appendix Table C1 presents the counties selected by this procedure and the resulting optimal weights.

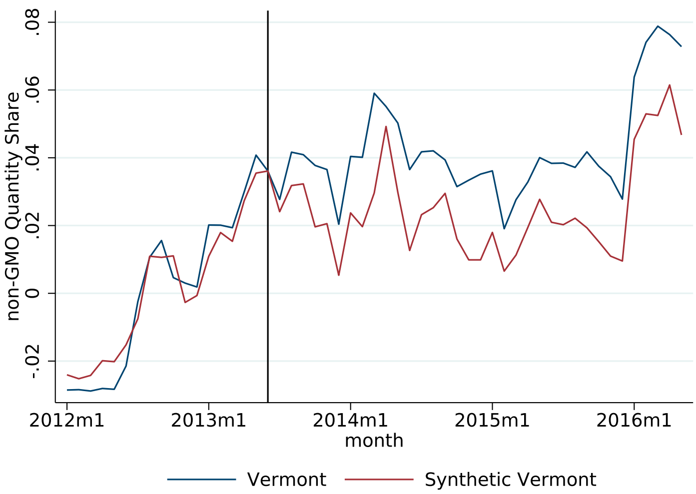
4.2.3. Empirical Specification and Results. The SC procedure does a good job constructing a measurably reliable control for Vermont from different counties in Maine. Figure 7 depicts the demeaned time series of non-GMO consumption trends in Vermont and Synthetic Vermont and highlights the fact that consumption trends are similar in the preperiod but diverge substantially in the postperiod. To quantify the difference in consumption between Vermont and Synthetic Vermont after the treatment, we specify and estimate the following baseline model, which is based on SC Doudchenko-Imbens Ferman-Pinto estimator (Doudchenko and Imbens 2016, Ferman and Pinto 2021):

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

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. The main coefficient of interest, δ, measures the difference in non-GMO product demand between Vermont and Synthetic Vermont in the posttreatment period.

The baseline specification results reported in the right panel of Figure 7 quantify the general patterns discussed previously. The results indicate an economically and statistically significant increase in the non-GMO quantity share in Vermont compared with Synthetic Vermont. To interpret the magnitude of the results, we calculate the local information elasticity of demand in a way similar to that described in Section 4.1, which yields $E^{VT}_{SVI} = 0.5$ (see Online Appendix C.3 for the calculation details). This implies that a 10% increase in Google SVI leads to a 5% increase in quantity share of non-GMO products.

Figure 7. (Color online) Demeaned Non-GMO Quantity Shares in Vermont vs. Synthetic Vermont



Synthetic Diff-in-Diff Results

	Quantity Share
Post × Vermont (δ)	0.0155***
	(0.0014)
Vermont (θ)	0.0147***
	(0.0010)
Month FE	Yes
Observations	102
R-squared	0.985

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 passed the House vote in Vermont. The time trends prior to demeaning are presented in Figure C1. Clustered standard errors reported in parentheses are Diff-in-Diff regression-based clustered standard errors. In Online Appendix C.8, we report bootstrapped standard errors following Arkhangelsky et al. (2021) and placebo-based standard errors following Abadie et al. (2010). The results remain unchanged.

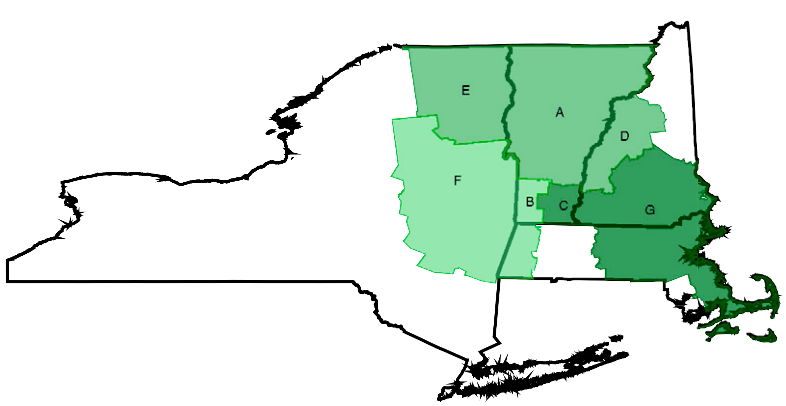
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

As in Section 4.1, we also formally test whether the outsized differential demand response in Vermont can be attributed to differential changes in marketing mix variables. We find no statistically significant divergence in assortment composition or pricing between Vermont and Synthetic Vermont in the post-treatment period (see Table C3).[12]

4.2.4. Information Source Test: DMA Border Areas. Next, we implement a test to understand the source of the local information effect documented above and, in particular, whether it was driven by traditional local media or by on-the-ground efforts within Vermont's borders. If the effect was driven by traditional media, we would expect a similar non-GMO demand response within any given DMA.

To answer this question, we estimate a geographically localized difference-in-differences (Diff-in-Diff) 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) in Vermont: (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 8, the largest DMA, Burlington (A+E+D), extends into New York

Figure 8. (Color online) Vermont DMA Map and Non-GMO Quantity Share Estimates



A+B+C vs. D+E+F

	Quantity Share
Post × Vermont (δ)	0.0128***
	(0.002)
Month FE	Yes
Store FE	Yes
Observations	15,364
R-squared	0.875

Notes. The top shaded area ($A + E + D$) is the Burlington DMA. A is within Vermont borders, whereas E and D are outside. Light shaded area is Albany-Schenectady-Troy DMA that also covers southwest Vermont (B). Dark shaded area is Boston DMA that also covers southeast Vermont (C). The table on the right reports estimates from a pooled regression of the specification in Equation (3). Clustered standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

(E) and New Hampshire (D); Albany-Schenectady-Troy DMA (B+F) extends into New York and Massachusetts (F); and Boston DMA (C+G) extends into New Hampshire and Massachusetts (G).

We compare consumption patterns in treated stores in regions A, B, and C, to control stores in regions D, E, and F. Using data pooled across all three DMAs, we estimate the following store-level Diff-in-Diff regression:

$$Y_{st} = \delta[I_{VT} \times Post_t] + \lambda_t + \mu_s + \varepsilon_{st}, \tag{3}$$

where Y_{st} is quantity share in month t and store s; I_{VT} is an indicator that takes a value of one if store s is located in Vermont, and zero otherwise; $Post_t$ is an indicator that equals one for months on or after May 2013; and λ_t and μ_s are month and store fixed effects, respectively. The right side of Figure 8 reports the estimation results. We find that the DMA regions that lie within Vermont exhibit a significantly larger increase in non-GMO consumption than the bordering regions of the same DMAs that lie outside Vermont. These results effectively rule out traditional media as the primary source of the information effect and strongly suggest that the on-the-ground efforts within Vermont increased consumer awareness and induced differential changes in consumption patterns. This interpretation is consistent with what we gleaned from interviews with two leaders from *Vermont Right to Know*, the coalition largely responsible for the anti-GMO movement in Vermont that paved the way for GMO labeling legislation. Their recount of the coalition's work supports our interpretation that local information efforts drove the differential consumer response in Vermont. For additional details about these interviews, see Online Appendix A.3.

In summary, we find similar information elasticities of demand for non-GMO products across the entire United States and Vermont (0.6 and 0.5, respectively). The context of each analysis differs: Section 4.1 analyzes the information effect generated from legislative activity *without* implementation, whereas Section 4.2 quantifies the effect *with* implementation. The unique setting in Vermont wherein the information environment begins to diverge *after* passage of the bill allows us to isolate the information effect attributable to the passage and implementation process of a mandatory GMO labeling law prior to labels appearing on products. Despite this distinction, the consistency of the two estimates suggests that GMO legislative activity, with or without implementation, generates a similar level of consumer awareness and indirect information effect at the margin.

5. Direct Effects of Mandatory GMO Labeling

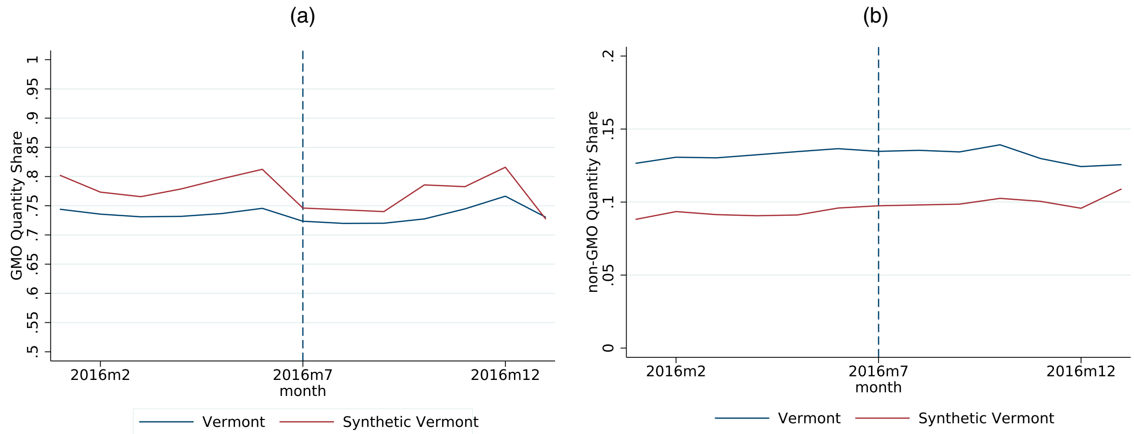
The two prior empirical analyses in Section 4 capture the indirect effects of mandatory GMO labeling policy, generated through heightened consumer awareness of GMO topics, on demand for non-GMO products. Recall that those results are identified using the sample period during which there were no GMO labels present on any products in stores. In this third part, we return to the quasi-natural experiment in Vermont to formally test whether the arrival of mandatory GMO labels had any additional *direct* effect on GMO and non-GMO demand in Vermont.

As we discuss in Section 2, GMO labels were added by Big 3 cereal companies nationwide and appeared on the shelves across the United States around the same time. We hypothesize that if the implementation of the law made consumers in Vermont more aware of the GMO label, or 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 gap in GMO quantity share between Vermont and Synthetic Vermont. Figure 9 depicts average GMO and non-GMO product quantity shares six months before and after implementation of the mandatory GMO law in July 2016. Visual inspection of this figure suggests no significant changes in GMO or non-GMO consumption patterns in Vermont. We investigate this relationship formally using two tests.

Our first test addresses the first hypothesis—whether there are any significant consumption changes *within* Vermont after mandatory GMO labeling took effect. We look at the difference in GMO and non-GMO quantity shares in Vermont (post- versus pretreatment). For this exercise, the treatment is the implementation of the mandatory GMO labeling law in July 2016. To isolate the direct GMO labeling effect, we specify the pretreatment period as January 2016 to June 2016 and the posttreatment period as July 2016 to December 2016 and estimate the first difference using weighted average state-level data as well as store-level data. Columns (1) and (3) in Table 5 report the state-level regression results, and columns (5) and (7) report the store-level regression results. We find supportive evidence that the consumption patterns in Vermont did not change in any statistically significant or economically meaningful way after the implementation of the labeling law.[13] Notably, the first difference point estimates are positive (albeit not statistically significant), which is the opposite of concerns raised by the food industry and of results found in prior experimental research (for meta analyses, see Lusk et al. 2005 and Dannenberg et al. 2009). Therefore, these results provide convincing evidence that market shares for GMO products did *not* decrease after mandatory GMO labeling took effect in Vermont.

The second test addresses whether GMO and non-GMO consumption patterns further diverge between Vermont and Synthetic Vermont after the law's implementation. To implement this test, we again use both

Figure 9. (Color online) Quantity Shares and Mandatory GMO Labeling Law Implementation



Notes. (a) GMO quantity share. (b) Non-GMO quantity share. This figure depicts GMO and non-GMO quantity shares in Vermont and Synthetic Vermont from January 2016 to December 2016. The quantity shares are aggregated to the state level using synthetic weights and averaged over three-month intervals. The dashed line indicates the month when GMO labeling law was implemented.

the state-level and the store-level GMO and non-GMO quantity share time series for Vermont and Synthetic Vermont. We estimate the Diff-in-Diff specification outlined in Equation (2) for the state-level sample. For robustness and to increase power, we also estimate the GMO label effects using store level data with store fixed effects (see Equation (1) in Online Appendix C.5 for more details).[14] Columns (2) and (4) in Table 5 report the state-level regression results, and columns (6) and (8) report the store-level regression results. For both GMO and non-GMO quantity shares, the results show that the estimated coefficient for δ is not statistically significantly different from zero. Thus, we again find no evidence of an additional effect on consumption of GMO or non-GMO products that can be attributed to the GMO label directly providing more information or to implementation of the law raising awareness of the label. In both tests, the null effect is robust to extending the postperiod to December 2017 (see Online Appendix D.1).

To summarize, the results of these two tests indicate that the implementation of GMO labeling in Vermont did not have any direct impact on consumer choices. Coupled with our main results, these findings imply that consumers who were receptive to altering their purchasing behavior to avoid GMO ingredients had likely already encountered alternative labels such as "Non-GMO Project 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.

Table 5. Direct Effects of Mandatory GMO Labeling Policy

	State level				Store level			
	GMO products		Non-GMO products		GMO products		Non-GMO products	
	(1) First Diff	(2) Diff-in-Diff	(3) First Diff	(4) Diff-in-Diff	(5) First Diff	(6) Diff-in-Diff	(7) First Diff	(8) Diff-in-Diff
Post	−0.0031		0.0034		0.0127		−0.0019	
	(0.0125)		(0.0036)		(0.0073)		(0.0026)	
Post × *Vermont*		0.0171		−0.0056		0.0003		0.0002
		(0.0194)		(0.0035)		(0.0024)		(0.0020)
Observations	12	24	12	24	432	816	432	816
R^2	0.006	0.877	0.084	0.980	0.653	0.761	0.895	0.927
Store fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes. In columns (1) to (4), the dependent variable is quantity share aggregated to state level separately for Vermont and Synthetic Vermont using the synthetic unit weights. In columns (5) to (8), the sample is at the store-month level. The First Diff regressions are weighted by store quantity weights. The Diff-in-Diff regressions are weighted by both the synthetic unit weights and the store quantity weights. Clustered standard errors in parentheses. For these regressions, the postperiod goes to the end of 2016. Extending the sample period to the end of 2017 yields similar results, which are reported in Online Appendix D.1.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

6. Discussion and Concluding Remarks

In this paper, we study the impact of mandatory GMO labeling on consumer preferences in a regime with established voluntary non-GMO labeling. We evaluate both the *direct* effect of mandatory GMO labels and the *indirect* awareness effect of GMO labeling policy initiatives on demand for GMO and non-GMO products. Our paper provides evidence that variation in consumer awareness around GMO topics across the United States induced statistically and economically significant changes in consumer behavior: We show that the increased adoption of products with voluntary non-GMO labels was particularly pronounced in states and time periods when mandatory GMO labeling legislation was considered, even if the proposed legislation was never implemented. Our results suggest that the market share of newly introduced non-GMO products would have been 36% lower if not for the additional awareness that was generated by legislative activity.

We then use a quasi-natural experiment in Vermont, the only state to implement mandatory GMO labeling in the United States, to examine the indirect impact of mandatory labeling legislation that was eventually implemented. Leveraging institutional details of the rollout of mandatory GMO labeling in Vermont, we use a synthetic control framework to show that uptake of non-GMO products increased more in Vermont relative to surrounding areas due to Vermont's unique information environment, which was triggered by on-the-ground efforts in preparation for the implementation of labeling after the law was passed. Last, we formally test whether the actual implementation of mandatory GMO labeling had any additional direct effect on demand for GMO and non-GMO products in Vermont and find no statistically discernible impact.

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 lobbying costs 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, which might be reasonable if firms see costly product reformulation to avoid GMOs as the only viable product strategy to mitigate these risks. Our findings suggest, however, that consumer movements and campaigns such as GMO labeling initiatives offer firms an opportunity to benefit from 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 in 2000, to which many firms responded by expanding their product portfolios to include both conventional and organic products. Analogously, with the rollout of the NBFDS, a similar strategy that caters to evolving consumer preferences may drive long-term growth in the burgeoning non-GMO product market, particularly in locations where such preferences are most pronounced.

The second important insight from our results pertains directly to national mandatory GMO labeling. Since January 1, 2022, all foods for sale in the United States are 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 additional effect on consumer behavior in the short run.

Our null result for the short-term direct effect of GMO labeling stands in stark contrast to existing experimental studies that show sizable effects. Using revealed preference data, 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. Therefore, relative to prior studies, our findings have greater external validity in predicting actual consumer response to the federal GMO labeling mandate. Furthermore, the fact that we find no short-term *direct* effect of mandatory GMO labeling on consumer demand is perhaps neither surprising nor concerning—well-established voluntary disclosure mechanisms already exist in the marketplace to facilitate consumer choice. This null result, however, should not be construed to suggest that the mandatory GMO labeling law had no *overall* effect. The underlying information mechanism we uncover at the core of our findings is in fact due to GMO labeling legislative activity, thereby emphasizing the importance of understanding the *indirect* market outcomes of policy initiatives as well.

As with every study, there are several limitations that present opportunities for future research. First, our data do 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 what 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 newly introduced non-GMO product adoption. In addition, the focus of this study is RTE cereal, a market characterized by an oligopoly structure and by highly recognizable brand names that generate strong brand loyalty among consumers. Although the RTE cereal category comprises a significant share of processed food manufacturing and is an important downstream market for GMO commodities, the effects of GMO and non-GMO labeling may differ in other food product markets with a different set of characteristics. Last, it is also important to qualify our findings in the context of short-term and long-term effects. Consumer preferences around the GMO attribute may continue to evolve over time, particularly as consumers learn more about GMOs under the mandatory disclosure regime. Over the last two decades, we have observed a similar evolution in the market for organic products over time.

Regarding the latter point, we would expect most of this change to be driven by the non-GMO market and the proliferation of voluntary non-GMO (NGPV) labeling, rather than mandatory GMO labeling, for several reasons. To begin with, the approved mandatory GMO on-package text label adopted by most firms to date is rather inconspicuous (see Figure A2) and 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 A1), for which we found no additional label effect after implementation. The design and presentation format of non-GMO and GMO labels play an important role in shaping consumer demand (Kim et al. 2022), and the less prominent placement of mandatory GMO labels, particularly when compared with boldly featured voluntary non-GMO labels, may have contributed to their lack of effectiveness. Furthermore, if this information is only accessible via QR code, as allowed under current legislation, many consumers may never actually observe the label.[15]

Moreover, it is not clear if 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. Lastly, firms producing non-GMO products have an incentive to invest in advertising and other forms of information disclosure to grow that segment. Based on the totality of these arguments and observations, we expect the direct effects of mandatory GMO labels to be limited.

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Endnotes

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

[2] Credence attributes 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 and GMO presence are examples of credence attributes.

[3] For the interested reader, Appendix A.1 provides additional legislative details on the state-level GMO labeling initiatives and a summary of the rule-making process and accompanying information campaigns in Vermont.

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

[5] 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.

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

[7] 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 with a total quantity share of 0.00095. Similarly, we also exclude two very small (by quantity share) products because their pricing patterns do not satisfy the identification assumption described below.

[8] The examples in Figure 4 illustrate Google SVI starting in 2013 because Non-GMO Product Verified product entry was practically nonexistent prior to that. We do not include California in (a) for this reason as well because it experienced GMO legislative activity in 2012 before most non-GMO product entry.

[9] We investigate multiple alternative specifications reported in Online Appendix B.2. The first specification uses month of entry fixed effects, instead of quarter fixed effects. The second specification limits the sample and focuses only on the seven states with GMO labeling legislative activity. To rule out the possibility of the information environment in Vermont driving these results, the third and fourth specifications replicate the main specification for all states excluding Vermont and for the seven states excluding Vermont, respectively. Across all specifications, the results are robust and suggest that legislative activity, even without passage and implementation of a law, can generate relevant awareness differences that affect demand. Finally, because most products entered in January 2016, we also estimate the main regression focusing on this subset of products and find similar results reported in Online Appendix B.4.

[10] To calculate the percentage increase in Google SVI in Vermont relative to Maine, we estimate a Diff-in-Diff regression on monthly SVI. Vermont's SVI time series designates treated units, while Maine's time series designates control units, and the treatment period is May 2013. The percentage change is calculated by dividing the $Post \times Treated$ coefficient by the preperiod average SVI in Maine.

[11] 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. Our results are robust to minor adjustments to this pre/post division point.

[12] We present a number of additional analyses and robustness tests in Online Appendix C. In Online Appendix C.2, we summarize non-GMO quantity shares in pretreatment and post-treatment periods across different sets of locations in Maine and Vermont (Table C2), and in Online Appendix C.5 we show a robustness test using a context in which pre-period quantity share levels are the same in Vermont and Maine. In Online Appendix C.5, we also estimate the synthetic Diff-in-Diff regression at the store level instead of state level, and we implement a different synthetic match procedure with multiple treated units, wherein we match (with replacement) each county in Vermont to the donor pool of Maine counties. Finally, in Online Appendix C.7, we examine the quantity share changes of organic products (products with the USDA Organic label but not the non-GMO label) and GMO products. The results from all these analyses and robustness tests are in line with the main results.

[13] In a different robustness test, we specify the treatment month as April 2016, the earliest possible month when GMO labels could have appeared in the stores (using treatment periods three months before and three months after) and get similar results.

[14] Consistent with the graphical evidence in Figure 9, we find no statistical evidence of non-parallel trends between Vermont and Synthetic Vermont during the narrower pre-period before label implementation, possibly because there were no notable new non-GMO product introductions during this period.

[15] There are four options provided by the USDA that are available for manufacturers to meet the NBFDS labeling requirements: (1) on-package text, e.g., *"Contains a bioengineered food ingredient"*; (2) USDA-approved symbols (see an example in Figure A3 in Online Appendix A.4); (3) electronic or digital links that include instructions to scan for more information; or (4) text-message disclosure (USDA Agricultural Marketing Service 2018).

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