Steering Consumers' Learning: Evidence from Stockout Substitutions in Curbside Pickup

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November 30, 2024

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Abstract

Items ordered for curbside pickup sometimes go out of stock. This obliges the store to choose substitutes on the affected consumers' behalf. Using novel data from a supermarket chain, I show that these "stockout substitutions" influence consumers' future purchases through the mechanism of learning. This presents the store with the following opportunity to increase its future profits: if the store selects substitutes from profitable brands that the consumers have never tried before, some of them will learn that they like the brands of their substitutes and then purchase these brands' products in the future. However, I find that consumers are less likely to accept such substitutes than they are to accept substitutes from brands they have previously purchased. To quantify the trade-off between steering consumers' learning and maximizing the probability that substitutes are accepted, I estimate a learning-based model of differentiated products demand. The gains from steering consumers' learning depend on their respective purchase histories as well as the extent of learning in the product category.

JEL Classification: D12, D83, L21
Keywords: Consumer learning, online shopping, differentiated products

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Special thanks to Michael Conlin, Kyoo il Kim, and Arijit Mukherjee for their advice about this project. I also thank Benjamin Bushong, Ying Fan, and seminar participants at the 2023 SEA Annual Meeting and the MSU Grand River workshop for helpful comments. Any remaining errors are my own. Additional thanks are extended to the retailer that supplied the data and provided information about the purchase environment. I am also grateful to dunhummby, which provided financial support, and to the Institute for Cyber-Enabled Research at Michigan State University, which provided computational resources and services.

1. Introduction

Consumers often make decisions with imperfect information. This has motivated an extensive literature on government information provision. Could the government increase consumers' welfare by providing easily accessible information? Researchers have found favorable evidence in a variety of settings. Take the case of grocery shopping. When the government requires that unhealthy products carry warning labels, consumers reduce their purchases of unhealthy products that they had mistakenly believed to be healthy (Barahona, Otero, and Otero 2023). Another example concerns health insurance. Here, the government can steer consumers towards high-quality insurance plans by publishing quality scores (Vatter 2024).[1]

Firms also steer consumers' learning.[2] But firms' incentives differ from those of the government; whereas the government steers consumers' learning to increase their welfare, firms steer consumers' learning to maximize profits. The resultant learning may, therefore, be suboptimal for consumers.

This paper explores how firms can optimally steer consumers' learning. I study this question in the context of curbside pickup. This is a "click-and-collect" form of shopping in which consumers order groceries online and then pick them up from their local supermarket. Sometimes, however, the store cannot supply an ordered item because it has gone out of stock. This obliges the store to select another item—known as a "stockout substitution"—to serve as a replacement. Once the consumer arrives, she can either purchase this suggested substitute, or reject it and buy no such item.[3]

Stockout substitutions sometimes cause consumers to try new products for the first time. What they learn about these products may influence their subsequent purchases. This enables the store to steer consumers' learning so that they are likelier to purchase high-margin (i.e., profitable) products in the future. To see the intuition, consider a consumer who customarily orders low-margin products. On one occasion, however, her preferred product goes out of stock. In its place, she is offered a high-margin product that she has never purchased before. If she accepts this substitute, she may discover that she likes it and, in consequence, purchase it on subsequent shopping trips. This would increase the store's future profits. However, less profitable outcomes are also possible. In particular, our consumer could reject this unfamiliar substitute and leave the store with zero earnings.[4]

[1] Concerning both food and health insurance, government information provision also causes a welfare-increasing response on the supply side. In particular, food manufacturers formulate healthier products (Barahona, Otero, and Otero 2023), while health insurers increase plan quality (Vatter 2024).

[2] Firms employ many methods to steer consumers' learning. One is advertising, which serves to inform consumers of a firm's product range (Anand and Shachar 2011) as well as to signal its quality level (Ackerberg 2003). Strategic pricing is another method of steering consumers' learning. By reducing its prices, a firm *encourages* consumers to try its own products (Osborne 2011) while *discouraging* them from trying its competitors' products (Ching 2010).

[3] Of course, she could also go into the store to search for a different substitute. However, the data suggest that this is quite rare.

[4] Although I strongly suspect that the store's handling of the stockout does *not* influence where the consumer shops in the future, I still explore this possibility in Sections 4 and 7.

Given the uncertainty involved, can the store increase profits by steering consumers' learning? To provide insight, this paper analyzes novel data from curbside pickup at a regional supermarket chain. I find evidence that stockout substitutions do, indeed, influence consumers' learning. Specifically, when consumers are offered substitutes from unfamiliar brands (by which I mean branded product lines, like the "Nature Valley" brand of granola bars), the consumers sometimes discover that they like their substitute's brand and purchase its products in the future. However, I also show that consumers tend to prefer substitutes that do not result in learning. Instead, they prefer substitutes that belong to brands they have previously purchased. This creates a strategic trade-off for the store. On the one hand, the store can exploit stockout substitutions to steer consumers' learning towards profitable brands, thereby increasing its future profits. On the other hand, consumers are more likely to reject stockout substitutes that belong to unfamiliar brands. To quantify this trade-off, I estimate a learning model of demand for differentiated products. Then I use the model to conduct counterfactual simulations. I find that optimal stockout substitution policy would increase the store's profits by 2.5% to 5.6% in the three product categories that I study.

This paper is, to my knowledge, the first to empirically characterize how a firm can optimally steer consumers' learning about *experience goods* (meaning goods whose utility must be learned through usage experiences).[5] The task proves unusually tractable here for two reasons. First, consumers' preferences over groceries, along with their learning, can be distilled in a comparatively simple demand model.[6] And second, general equilibrium effects are negligible so far as stockout substitutions are concerned. That is to say, the focal store's optimal substitution policy is not influenced by those of its competitors.[7]

The remainder of the paper proceeds as follows. Section 2 provides institutional background and then introduces the data. I study a supermarket chain that offers three ways to shop: in-person, home delivery, and curbside pickup. The "stockout substitutions" of interest occur in the last of these shopping channels. For each such substitution, I observe the out-of-stock item and the substitute, as well as the consumer's decision to accept or reject the substitute. Besides the data on stockout substitutions, I also observe "scanner data" that record consumers' purchases at the store. Importantly, the scanner data are at the household-panel level, so I can compare someone's purchases before versus

[5] I am only aware of one other study that empirically characterizes the optimal supply-side strategy to steer consumers' learning about goods of any description—experience or otherwise. Compiani et al. (2024) consider how online platforms like Expedia should rank products in web searches, given that consumers possess incomplete knowledge of products' *observable* characteristics. The assumption is that consumers will learn a product's true utility once they have clicked on its web page, which describes the product's observable characteristics.

[6] Because packaged foods are highly standardized and have just one usage case (namely, snacking), I adopt a "one-shot" model of learning in which consumers learn their true tastes for products after trying them just once. In addition, grocery shopping is characterized by many fast-paced but low-stakes decisions. I therefore approximate consumers' behavior as being myopic, as opposed to forward-looking.

[7] As previously mentioned, it seems unlikely that consumers choose where to shop based on grocery stores' handling of stockout substitutions. See Sections 4 and 7 for further discussion.

after a stockout substitution.

In Section 3, I present descriptive evidence of the trade-offs faced by the store as it chooses stockout substitutes. I begin by examining why substitutes are accepted or rejected. It emerges that the probability of acceptance is increasing in the similarity of the substitute's observable characteristics—such as brand or size—to those of (i) the out-of-stock product and (ii) products that the consumer has previously purchased. Take the characteristic of brand, for example. Within the three product categories that I study, a substitute is 2.1 to 4.1 percentage points more likely to be accepted if it shares the brand of the out-of-stock product than if it does not. Likewise, a substitute is 0.5 to 7 percentage points more likely to be accepted if it shares the brand of a past purchase than if it does not. In the next set of descriptive exercises, I ask whether stockout substitutions influence consumers' future purchases through the mechanism of learning. I find evidence that consumers learn about their tastes for substitutes' *brands*. When consumers are offered a substitute that belongs to a brand they have never purchased before, they are more likely to purchase that brand's products in the future (compared to the counterfactual where no stockout occurred). Specifically, being offered a substitute from an unfamiliar brand increases the fraction of future purchases that share the substitute's brand by between 0.8 percentage points (frozen french fries) and 2.6 percentage points (granola bars). By contrast, I do not find comparable evidence that consumers learn about their tastes for other characteristics, such as size. This is intuitive; consumers are unlikely to learn much from, say, trying a 16-pack of granola bars for the first time. Finally, I study the determinants of products' profitability, as measured by retail margins (i.e., retail price minus wholesale cost). I find that a product's brand is among the primary determinants of its retail margin.

Taken together, these empirical patterns create a strategic problem for the store. On the one hand, it can exploit substitutions to introduce consumers to high-margin brands that they have never tried before. Some of these consumers will learn that they like their substitute's brand and purchase its products in the future. On the other hand, consumers tend to prefer substitutes that share the brand of the out-of-stock product (or that of a previous purchase). So if the consumer is offered a substitute from an unfamiliar brand, she may be disposed to reject it.

How should the store's substitution policy navigate this trade-off? To build intuition, I present a conceptual model in Section 4 that formalizes the store's strategic problem in a simplified setting. Then, in Section 5, I propose an empirical model of demand under consumer learning. In the model, consumers are unsure of their tastes for a given brand until they purchase one of its products. Consumers' prior beliefs about their tastes for brands, along with their true tastes, are heterogeneous.

The estimated model parameters are reported in Section 6. With these in hand, I can simulate the store's profits under counterfactual substitution policies. My goal is to characterize the "optimal" substitution policy, meaning the one that maximizes the present-discounted value of expected profits. I find that the optimal policy increases profits by 5.6% with respect to consumers who suffer stockout substitutions for granola bars. The corresponding gains are 2.5% and 2.4% for flavored milk and frozen french fries, respectively. Not all of these gains stem from steering consumers' learning, however; the optimal policy also increases the store's expected profits on the *present* shopping trip. In particular, the optimal policy tends to prescribe higher-margin substitutes than does the store's existing policy. Although consumers are less likely to accept these high-margin substitutes, the increase in margins exceeds (in percentage terms) the decrease in acceptance probabilities. This raises the following question. To what extent do the gains under the optimal policy stem from steering consumers' learning, as opposed to boosting present-trip profits? It emerges that steering consumers' learning plays the largest role for the product category of granola bars. This finding is rooted in the demand estimates, which suggest that consumers learn more about granola bars than they do about flavored milk or frozen french fries. Furthermore, within the product category of granola bars, the gains from steering consumers' learning are concentrated in stockouts where the consumer has *only* purchased the budget brand in the past. In the optimal substitution policy, the store exploits stockout substitutions to introduce these consumers to higher-margin mainstream brands. The resultant learning contributes more than a fifth of the gains provided by the optimal policy in regard to these consumers.

2. Institutional Details and Data

A. Curbside Grocery Pickup

In curbside pickup, consumers order groceries online and later pick them up from bricks-and-mortar supermarkets. This form of grocery shopping gained traction during the COVID-19 pandemic (Young 2023) and remains popular, with US sales exceeding $3 billion in February 2024 (Brick Meets Click and Mercatus 2024).

To see how curbside pickup works, picture a consumer who wants to purchase two items: granola bars and flavored milk. She begins by visiting the store's app or website. When she searches for a specific item—such as "granola bars"—she sees a list of relevant products, along with prices, images, and written descriptions. Once she identifies her preferred product—say, Sunbelt Sweet & Salty granola bars—she adds it to her virtual "shopping cart." Having repeated this process for flavored milk—choosing, say, Fairlife chocolate milk—she completes the order by indicating the time when she plans to pick up her groceries (for example, "Tomorrow morning, 8 a.m. – 9 a.m.")

Once the consumer is ready to pick up her groceries, she drives to the store and parks in a designated "curbside pickup" area. A store worker then brings the groceries out to her car, where she pays for them. Importantly, the store maintains the same prices online as in-store;[8] our consumer will pay the

[8] If a consumer places a curbside order such that the sum of the ordered items falls below a specified threshold, she will pay a fixed fee for curbside pickup.

same price for a given item as if she had physically entered the store and purchased it there.

Stockout Substitutions.—The store is sometimes unable to supply an ordered item because it has gone out of stock. In that event, the store will offer a similar item to serve as a substitute.

To illustrate how stockout substitutions proceed, let us revisit the (hypothetical) consumer who has ordered granola bars and flavored milk. Sometime *after* she places her order but *before* her intended pickup time, a store worker will collect the ordered items and set them aside (so that they can be brought out immediately upon her arrival). As he does so, the worker may discover that an ordered item has gone out of stock. Imagine, for instance, that our consumer's preferred granola bars—namely, Sunbelt Sweet & Salty—are unavailable. To ensure that she is not left without granola bars altogether, the worker will choose another product to serve as a substitute—say, Nature Valley Sweet & Salty granola bars.[9] Then, when our consumer arrives at the store,[10] she will be presented with two options: either she can accept the substitute that the worker chose earlier on her behalf, or she can reject it and buy no such product at all. If she accepts the substitute, she will pay the substitute's price (not that of the out-of-stock product).

B. Data

This study employs data from a regional supermarket chain that offers both in-person and online shopping. Concerning the latter, consumers can choose whether they prefer curbside pickup or home delivery.[11] (My analysis focuses on the former shopping channel as, in the latter, consumers select stockout substitutes themselves.[12])

The supermarket data consist of three distinct data sets. These include: (i) the "curbside stockout" data set, which details stockout events in curbside pickup; (ii) the "scanner" data set, which records consumers' final purchases; and (iii) the chain's product catalog, which describes the products carried by the chain. I will now describe each of these data sets in turn.

Curbside Stockout Data.—The first data set describes (attempted) stockout substitutions in curbside pickup from February 2020 to March 2022. Each observation includes the universal product code

[9] The store's website and mobile app allow the consumer to leave item-level instructions for the store. For instance, someone who is ordering strawberries might request "extra-ripe" berries. However, a consumer could also use this feature to request a specific substitute if her preferred product goes out of stock. Although I do not observe whether a consumer makes such a substitution request (or, for that matter, whether she leaves item-level instructions of any kind), the retailer has indicated that, during the time period of my data, consumers almost never leave item-level instructions.

[10] Since September 2021, the store has also allowed consumers to accept or reject substitutes remotely. When an ordered item goes out of stock, the affected consumer receives a pop-notification or text to that effect, along with information about the substitute (such as the name and price). She can then accept or reject the substitute using her phone or computer. (If she fails to respond electronically, she will be offered the substitute at her car as in the old procedure.)

[11] Home delivery resembles curbside pickup as far as orders are concerned. Unlike curbside pickup, however, home delivery does not require the shopper to travel to the store. Rather, her groceries are delivered directly to her home. For this convenience, she must pay a fee. (By contrast, curbside pickup is free for sufficiently large orders.)

[12] When an item ordered for home deliver becomes unavailable, the store phones the shopper to determine her preferred replacement.

(UPC) of both the out-of-stock product and the substitute. I also see the price of the substitute,[13] and whether it is accepted or rejected by the consumer.

Importantly, each observation in the data contains the loyalty ID number of the affected consumer,[14] along with the date, time, and store location of pickup. This information enables me to identify the consumer's past and future purchases within the scanner data set (as described below).

To see what the curbside stockout data look like in practice, turn to Appendix Table 1, which depicts the observations that would result from the stylized example in Section 2A.

*Scanner Data.—*The second data set records all purchases at the chain, both online and in-person, between April 2016 and July 2023. Each observation, which consists of a single transaction, includes the UPCs and prices of all the items that were purchased, along with the consumer's loyalty ID. The data also record the date, time, and store location of the transaction. Finally, I observe the wholesale costs of each item.[15] Hence, by taking the difference between purchase prices and wholesale costs, I can recover the "retail margin" of each item carried by the store.

Where curbside pickup is concerned, the scanner data only include a stockout substitute if it is accepted by the consumer. To illustrate, consider once more the (hypothetical) consumer from the preceding subsection. Recall that she ordered Sunbelt Sweet & Salty granola bars and Fairlife chocolate milk, but that the former went out of stock. Here, the substitute granola bars (Nature Valley Sweet & Salty) would only appear in the data if she accepted the swap. By contrast, the chocolate milk would certainly appear in the scanner data, as it is the exact product that she had originally requested. See Appendix Table 2 for a comparison of the data entries that would result from acceptance versus rejection.

Regarding stockout substitutions, the scanner data enable me to infer the price of the out-of-stock product. To do so, I search the scanner data for purchases of the relevant product on the same day, and at the same store, as the intended pickup—either before or after the stockout event. Provided that I locate at least one such observation, I approximate the out-of-stock product's price as being the mean of the observed purchase prices. If I do *not* observe any purchases of the product on the same day (and at the same store) as the substitution, I instead compute the mean purchase price on the day *before* the substitution.[16] Failing that, I approximate the out-of-stock product's price by taking the average purchase price on the nearest date for which observations appear in the data. If I have still not obtained the out-of-stock product's price, I compute the average purchase price for stores in the same

[13] The price of the out-of-stock item is obtained from the scanner data (as I will explain shortly).

[14] Participation in the chain's loyalty program is required to place curbside pickup orders.

[15] Prior to 2021, the retailer's cost measure included some fixed costs in addition to the wholesale cost. There are six months during which both the old cost measure and the new one (i.e., wholesale cost alone) are recorded. For individual products, I observe these two cost measures moving roughly in tandem during this period.

[16] Whereas it is possible for a consumer to place an order the day before pickup, it is impossible for her to place the order the day after! Thus, the average purchase price on the day before the pickup is likely more representative of the price that she expected to pay than is the average purchase price on the day after.

(narrowly-defined) geographic area on the nearest date with observations in the data (once more, up to seven days before or after the stockout event). The assumption is that stores in the same geographic area will coordinate on discounts (which might be advertised through mass mailings or billboards). To group stores by location, I rely on the most granular geographic designation in the chain's internal system.

Product Catalog.—The third data set describes the products sold by the chain. For each product, the catalog lists the universal product code (UPC) and the brand, as well as the location within the chain's product taxonomy. I also observe a string description of the product that characterizes its observable characteristics. To illustrate, here is a string description of a granola bar product:

"NV SWT/SALTY BAR PEANUT 6CT/1.2OZ"

This description indicates that the granola bars are sold under the Nature Valley brand, that they are "sweet and salty" flavored (with peanuts), and that there are six bars in total (each 1.2 oz). I employ so-called "regular expressions" to extract this information. Sometimes, however, a product's string description omits one or more characteristics of interest. In such cases, I consult either the manufacturer's website or that of a retailer that carries the product.[17] (One exception is the caloric content of granola bars, which I obtain from the nutrition data set constructed by Harris-Lagoudakis [2022].)

C. Summary Statistics

In the remainder of this paper, I focus on three product categories: flavored milk, frozen french fries, and granola bars. These categories were chosen for three reasons. First, each category consists of *experience goods*. That's to say, consumers do not innately know their preferences among goods within these categories. Rather, they learn their preferences through usage experiences. Take the case of granola bars, for instance. Suppose there exists a consumer who always purchases Sunbelt Sweet & Salty granola bars. Until she tries other products—such as different flavors of Sunbelt granola bars or different brands altogether—she cannot be sure that Sunbelt Sweet & Salty granola bars maximize her utility.

The second criterion by which I select product categories is the number of stockout substitutions. When I observe many stockout substitutions within a single category, it is easier to identify the extent to which the store's choice of substitute influences (i) the probability of the substitute's being accepted and (ii) the consumer's learning.

The last criterion is the complexity of the observable characteristics that differentiate products in the category. Consumers' preferences should mostly depend on a handful of characteristics (brand,

[17]Concerning the product category of granola bars, there are three products for which I failed to recover one observable characteristic: the total number of bars in the package.

size, flavor, etc.). For, when estimating demand, the computational burden is increasing in the number of characteristics. This rules out product categories like ice cream, where consumers' preferences pivot on dozens of different characteristics.[18]

Table 1 presents summary statistics for the three product categories studied. Within each category, between 13,000 and 41,000 households experience at least one stockout substitution in a curbside pickup order. As for the chain's product offerings, consumers can choose among many products and brands. This is especially true of granola bars, where more than five hundred (thirty) distinct products (brands) are purchased. Only a subset of the products or brands in a given category, however, are ordered for curbside pickup. The reason is that low-volume products are only available for in-store purchase.

Turning to the panel dimension of the data, Panel B characterizes the purchases of individual households that experience at least one stockout substitution. Depending on the product category, I observe an average of twenty-one to forty-one shopping trips per household. Five to ten of these shopping trips are curbside pickup (as opposed to in-store shopping or home delivery).

The typical household does not purchase the same "go-to" product on every shopping trip, but rather purchases a variety of brands and products. This is especially true of granola bars: the average household purchases seventeen (five) distinct products (brands). Regarding flavored milk, by contrast, the average household buys fewer than six (three) distinct products (brands).

Turning to stockout substitutions, Panel C indicates that between 17,000 and 66,000 (attempted) substitutions are observed in each product category. The probability of acceptance ranges from 85.0% (granola bars) to 90.6% (frozen french fries).

One stockout event can cause multiple stockout substitutions, if multiple consumers order the same product from the same store at roughly the same time. How often do stockouts occur, and how long do they last? To answer these questions, I join the curbside stockout data with the scanner data and then sort the combined data set by store, product, and date. For each store-product pairing in the resulting data set, I observe sequences of successful purchases (from the scanner data), interspersed with sequences of stockout substitutions (from the curbside stockout data). Treating the former as evidence that the product is in stock and the latter as evidence of stockout, I identify the *last* successful purchase before each stockout event as well as the *first* successful purchase afterwards. By computing the time elapsed between these two successful purchases, I obtain an upper bound on the duration of the stockout event.

Panel D reports the results of this descriptive exercise. The total number of stockout events varies across product categories, ranging from 14,000 (flavored milk) to 53,000 (granola bars). The median upper bound on the duration of an individual stockout event is between sixty and one-hundred

[18]The top-selling ice cream products feature many flavors (chocolate, coffee, cherry, etc.) and mix-ins (cookie dough, peanut butter, fudge, etc.)

Table 1 – Summary Statistics by Product Category

Statistic	Flavored milk	Frozen french fries	Granola bars
	Panel A. Overview		
No. of households with 1+ substitutions	13,014	30,588	40,115
No. of distinct products purchased	125	70	519
. . . of which ordered for curbside pickup	79	39	322
No. of distinct brands purchased	27	11	33
. . . of which ordered for curbside pickup	24	8	24
	Panel B. Per household with 1+ substitutions		
No. of shopping trips	40.7	21.7	37.0
. . . of which curbside pickup	9.5	5.7	8.1
. . . of which feature 1+ substitutions	1.3	1.3	1.5
No. of distinct products ever purchased	5.5	7.2	16.9
. . . of which ordered for curbside pickup	2.1	3.0	4.7
No. of distinct brands ever purchased	2.8	2.8	4.3
. . . of which ordered for curbside pickup	1.5	1.7	2.1
	Panel C. Stockout substitutions		
No. of (attempted) substitutions	17,484	39,397	65,608
Prob. accept (%)	88.0	90.6	85.0
	Panel D. Frequency and duration of stockout events		
No. of stockout events	14,710	28,884	52,740
Median upper bound on duration (hours)	60.4	124.0	136.1

Notes: Unless otherwise indicated, estimates are reported as means or totals. I follow the retailer's internal system in defining brands (see Section 3 for discussion). Appendix A describes how I obtain a very rough (and upwardly biased) approximation of stockout duration.

thirty-seven hours.[19]

State Dependence in Consumers' Purchases.—In Section 3B, I will present quasi-experimental evidence that stockout substitutions influence consumer learning. This evidence is based on comparisons of consumers' purchases before versus after a stockout substitution.

When reviewing these results, it helps to have an overall picture of state dependence in consumers' shopping choices. Do consumers tend to purchase the same products in consecutive trips? Or at least products of the same brand?

Appendix Table 3 presents summary statistics on state dependence in consumers' purchases. When

[19] I report the median, not the mean, because some "stockouts" are of such long duration that they are probably not stockouts per se. Rather, the store has likely dropped the product in question for several months and then reintroduced it.

shopping for flavored milk, there is a 60.3% probability that a consumer purchases the same product as she did the last time. The corresponding probabilities of repeat purchases are smaller for the other product category categories: 36.4% for frozen french fries and 38.2% for granola bars. At a coarser level, consumers typically purchase products that belong to the same brand on consecutive shopping trips, with probabilities ranging from 68.6% (granola bars) to 76.9% (frozen french fries).

3. Descriptive Evidence

In this section, I present descriptive evidence of the trade-offs faced by the store as it selects stockout substitutes. First, I highlight key predictors of a substitute's acceptance or rejection by the consumer. I find that the probability of acceptance is increasing in the number of observable characteristics (such as brand or size) that the substitute shares with either (i) the out-of-stock product or (ii) products that the consumer has previously purchased. Next, I present quasi-experimental evidence that the store's choice of substitute can influence consumers' learning about brands (by which I mean branded product lines, like the Quaker line of granola bars). Finally, I study the relationship between a product's observable characteristics and its retail margin (i.e., retail price minus wholesale price). I find that a product's brand is among the most important determinants of its retail margin.

Taken together, these empirical patterns create a strategic problem for the store as it chooses stockout substitutes. On the one hand, it can exploit substitutions to introduce consumers to high-margin brands that they have never purchased before. Some will learn that they like the high-margin brand more than they had expected and, in consequence, purchase its products on future shopping trips. On the other hand, consumers seem to prefer substitutes that are sold under brands that they have previously purchased. So, if the store offers substitutes whose brands are unfamiliar, consumers may be likelier to reject them—or even to reduce their future patronage of the store.

A. Why Do Consumers Accept or Reject Stockout Substitutes?

Whether a substitute is accepted or rejected can influence the store's earnings in both the present and the future. Consider first the case where the substitute is rejected. Regarding the present transaction, the store does not earn any retail margins on the substitute item. As for future profits, rejection signals that the consumer is unhappy with the store's handling of the substitution. Her dissatisfaction, in turn, may dent the store's future earnings if she reduces her future patronage as a result. Now turn to the case where the substitute is accepted. Concerning the present transaction, the store earns the retail margin associated with the substitute product. As to future profits, the consumer may, or may not, be happy with the store's handling of the substitution—and may, or may not, decrease her future patronage accordingly. Additionally, the consumer will learn whether she likes or dislikes the

Table 2 – Probability of Acceptance by Substitute's Similarity to Out-of-Stock Product

Characteristic	Whether shared by sub and out-of-stock product	Prob. accept	Obs.
	Panel A. Flavored milk		
Brand	Shared	0.899	8908
	Not shared	0.861	8576
Flavor	Shared	0.885	16,970
	Not shared	0.722	514
Pct. milk fat	Shared	0.894	12,368
	Not shared	0.847	5116
Size (oz.)	Within 10%	0.868	12,134
	Differs by >10%	0.909	5350
Whether high-protein	Shared	0.883	17,089
	Not shared	0.780	395
	Panel B. Frozen french fries		
Base vegetable	Shared	0.908	39,047
	Not shared	0.691	350
Brand	Shared	0.918	28,040
	Not shared	0.877	11,357
Flavor	Shared	0.910	33,595
	Not shared	0.884	5802
Size (oz.)	Within 10%	0.914	13,855
	Differs by >10%	0.902	25,542
	Panel C. Granola bars		
Brand	Shared	0.856	49,598
	Not shared	0.835	12,864
Calories	Within 10%	0.875	24,409
	Differs by >10%	0.824	11,792
Flavor	Shared	0.885	25,968
	Not shared	0.828	36,494
No. of bars	Within 10%	0.856	41,331
	Differs by >10%	0.843	21,131
Texture (chewy vs crunchy)	Shared	0.858	59,279
	Not shared	0.746	3183

Notes: This table compares the probability of acceptance when the substitute and the out-of-stock product share a given characteristic with the corresponding probability when they do not. For the product category of granola bars (Panel C), there are some observations where the caloric content and/or the number of bars of the substitute and/or the out-of-stock product are missing. Such observations are omitted from the table entries concerning these characteristics.

substitute product, provided that she has not already purchased it previously (in which case she will already know whether the product is to her taste). This learning, in turn, may alter her subsequent purchases (and ultimately the store's future profits).

The goal of this subsection is to understand *why* consumers accept or reject stockout substitutes. I focus on two key determinants of acceptance: the substitute's similarity to the out-of-stock product, and the substitute's similarity to products that the consumer has purchased on previous shopping trips.

The Substitute's Similarity to the Out-of-Stock Product.—Intuitively, the probability of acceptance should be increasing in the similarity of the substitute's observable characteristics (such as its brand or size) to those of the out-of-stock product. Because the out-of-stock product is the consumer's "first choice," products with similar observable characteristics should also be appealing.

To test this intuition, Table 2 compares the probability of acceptance when the substitute and the out-of-stock product share a given observable characteristic with the corresponding probability when they do not. The table is organized so that each the leftmost column lists the observable characteristics that differentiate products within the relevant product category. For example, flavored milks (Panel A) are differentiated with respect to five characteristics: brand; flavor (chocolate, strawberry, vanilla, etc.); percent milk fat; size; and being high-protein or not. There are two rows per characteristic. The upper row reports the probability of acceptance conditional on the substitute's sharing the relevant characteristic with the out-of-stock product, while the lower row indicates the corresponding probability conditional on the substitute's *not* sharing that characteristic. Concerning continuous characteristics (like size), I assume that the substitute and the out-of-stock product are essentially indistinguishable with respect to the characteristic if the two products differ by less than 10%.[20]

Two patterns emerge in Table 2. First, a substitute is likelier to be accepted if it shares a given characteristic with the out-of-stock product than if it does not. This empirical pattern holds, and is statistically significant at the 1% level, for all product categories and characteristics save one.[21] As for the second pattern, consumers attach greater importance to some characteristics than others. Take the case of frozen french fries, for example. So far as this product category is concerned, consumers seem to care more about the substitute's base vegetable (such as potatoes or sweet potatoes) than its size (in ounces). Whereas a substitute is 21.6 percentage points more likely to be accepted if it shares the base vegetable of a past purchase, it is only 1.2 percentage points more likely to be accepted if it

[20]Regarding one such continuous characteristic—namely, the caloric content of granola bars—some observations omit information on the substitute and/or the out-of-stock product. This is because the nutrition data set provides only partial coverage of the products carried by the chain. Consequently, the entries corresponding to calories in Table 2 reflect only the observations where the nutritional content of both the substitute and the out-of-stock product are known (roughly 58% of all observations.)

[21]The lone exception concerns the size of flavored milks: consumers are more likely to accept if the substitute's size perceptibly differs from that of the out-of-stock product than if it does not. This probably reflects the inverse probability between the substitute's matching the size of the out-of-stock product and its matching other characteristics. (See Zeyveld [2024].)

(approximately) matches the size of a past purchase.

The Substitute's Similarity to the Consumer's Previous Purchases.—Out-of-stock product aside, the consumer's purchases on past shopping trips may also point to her preferences for a substitute. In particular, the probability of acceptance should be increasing in the substitute's similarity to products that she has previously purchased. To test this hypothesis, Table 3 compares the probability of acceptance when the substitute does, or does not, share a given characteristic with *at least one* product previously purchased by the consumer.

I employ consumers' loyalty ID numbers to identify their past purchases. To illustrate, consider a consumer who experiences a stockout substitution within the product category of granola bars. Concentrating on the characteristic of texture (i.e., chewy versus crunchy), imagine that the hypothetical consumer has been offered *chewy* granola bars as a substitute. Here, I would locate all granola bar purchases in the scanner data that (i) feature the consumer's loyalty ID number and (ii) occur prior to the date and time of the stockout substitution. Then I would check whether any of these previously-purchased granola bars are chewy in texture (like the substitute product).

The results in Table 3 are intuitive: a substitute is more likely to be accepted if it shares a given characteristic with a previously-purchased product than if it does not. This is true of nearly all product categories and characteristics.[22] Once more, some characteristics seem to loom larger in consumers' decisions than others do. Concerning granola bars, for example, consumers seem to care more about substitutes' flavor (e.g., "oats and honey" or "chocolate chip") than about substitutes' caloric content. Whereas a substitute is 7.7 percentage points more likely to be accepted if it shares the flavor of a past purchase, it is only 0.3 percentage points more likely to be accepted if it (approximately) matches the caloric content of a past purchase. As for statistical significance, the association between (i) the substitute's sharing a given characteristic with products purchased on past shopping trips and (ii) the probability of acceptance is significant at the 1% level with only one exception.[23]

Reduced-Form Regressions.—I have presented suggestive evidence that consumers prefer substitutes that share characteristics with either (i) the out-of-stock product or (ii) products purchased on past shopping trips. However, these two predictors are probably correlated, because consumers frequently purchase products with characteristics they like (such as particular brands or flavors). What is the relative importance of the substitute's similarity to the out-of-stock product, versus its similarity to previous purchases? In Appendix B, I estimate a probit model in which the probability of acceptance depends on both of these factors. The results confirm that the probability of acceptance is increasing in

[22]There are two exceptions: for flavored milk (Panel A), size; and for granola bars (Panel C), the number of bars. These counterintuitive patterns (which are not statistically significant) probably reflects the inverse correlation between the substitute's sharing one characteristic with the out-of-stock product and its sharing another. (See Zeyveld.)

[23]The lone exception concerns french fries and, within that category, the characteristic of base vegetable. Although substitute french fries are 0.9 percentage points more likely to be accepted if they share the base vegetable of a product purchased on a previous shopping trip, this association is not statistically significant.

TABLE 3 – PROBABILITY OF ACCEPTANCE BY SUBSTITUTE'S SIMILARITY TO PAST PURCHASES

Characteristic	Does sub share characteristic with past purchase?	Prob. accept	Obs.
	Panel A. Flavored milk		
Brand	Yes	0.925	8725
	No	0.855	7159
Flavor	Yes	0.897	15,270
	No	0.811	597
Pct. milk fat	Yes	0.913	10,648
	No	0.854	5227
Size[a]	Yes	0.891	11,278
	No	0.898	4606
Whether high-protein	Yes	0.894	15,672
	No	0.816	212
	Panel B. Frozen french fries		
Base vegetable	Yes	0.916	30,020
	No	0.911	1410
Brand	Yes	0.930	18,684
	No	0.896	12,746
Flavor	Yes	0.918	26,498
	No	0.906	4932
Size[a]	Yes	0.917	29,989
	No	0.896	1441
	Panel C. Granola bars		
Brand	Yes	0.857	19,034
	No	0.839	15,389
Calories[b]	Yes	0.856	15,494
	No	0.853	4564
Flavor	Yes	0.894	13,083
	No	0.817	19,123
No. of bars[c]	Yes	0.847	24,058
	No	0.852	10,368
Texture (chewy vs crunchy)	Yes	0.852	30,585
	No	0.819	3838

Notes: This table compares the probability of acceptance when the substitute does, or does not, share a given characteristic with at least product that the consumer has previously purchased.

both (a) the substitute's similarity to the out-of-stock product, conditional on its similarity to products purchased on past shopping trips; and (b) the substitute's similarity to products purchased on past shopping trips, conditional on its similarity to the out-of-stock product.

B. Stockout Substitutions and Consumers' Learning about Brands

This subsection supplies descriptive evidence that stockout substitutions can influence consumers' learning. Throughout, I adopt the simplifying assumption that consumers learn about their tastes for products' observable characteristics, as opposed to their tastes for individual products. This simplifying assumption aligns my descriptive analysis with the demand model estimated in Sections 5 and 6. There, as is customary in the empirical IO literature (see Berry and Haile [2021]), I model consumers' utility as a function of observable product characteristics.

How might consumers learn about their tastes for products' observable characteristics? Consider a (hypothetical) consumer who always orders Sunbelt Sweet & Salty granola bars. Now suppose that these granola bars go out of stock and that our consumer is offered Nature Valley Oats & Honey granola bars as a substitute. If she accepts, she will learn about her tastes for two observable characteristics: brand, as she will try the Nature Valley brand for the first time; and flavor, as she will experience oats-and-honey–flavored granola bars for the first time (as opposed to the sweet-and-salty–flavored granola bars that she previously purchased). Importantly, the amount of learning may vary by characteristic, as consumers probably hold more accurate prior beliefs about their tastes for some characteristics than others. Intuitively, granola bar buyers are more likely to learn about their preferences for brands or flavors than they are to learn about, say, their preferences for the size of the package (meaning the number of granola bars).

The task of this subsection is, therefore, to determine how (if at all) stockout substitutions cause consumers to learn about their tastes for products' observable characteristics. I start by identifying stockouts where the consumer will learn about her tastes for one of the substitute's observable characteristics if she accepts. For example, if I were interested in the characteristic of brand, I would find stockout substitutions in which the substitute's brand is one that the consumer has never purchased before. Then, having identified stockout substitutions that enable consumers to learn about a specific characteristic, I tally how often their future purchases share this characteristic with the substitute. If stockout substitutions cause consumers to learn, the following empirical pattern should emerge. Of the consumers who accept the offered substitute—thereby learning their true tastes for its version of the characteristic—some will discover that they like the substitute's version more than they had expected. Consequently, a disproportionate share of their future purchases may feature the substitute's version of the characteristic, compared to the counterfactual where they never learned about this version. But how can I identify this counterfactual? That is, what would these consumers' purchases have looked like if they had never experienced the stockout substitution and, as a result, never learned about the substitute? To approximate consumers' future purchases in the absence of stockout substitutions, I identify "control consumers" who order the same products as the focal consumers. Unlike the focal consumers, though, these control consumers pick up shortly before the stockout event, and therefore do not learn about the substitute.

As I spell out my empirical strategy, it helps to focus on just one observable characteristic. I will, therefore, concentrate initially on the characteristic of brand and then explain how my strategy generalizes to other characteristics.

The intuition of this descriptive exercise is as follows. Consider once more the (hypothetical) consumer who always buys Sunbelt Sweet & Salty granola bars. Now assume that she is offered Nature Valley Sweet & Salty granola bars as a stockout substitute. If she accepts, she will consume Nature Valley-branded granola bars for the first time, thereby learning whether she likes or dislikes the Nature Valley brand. Now suppose that she does accept and, moreover, that she starts to purchase Nature Valley-branded granola bars (rather than Sunbelt) on her subsequent shopping trips. This shift in her purchases—from Sunbelt- to Nature Valley–branded granola bars—reflects two factors: (i) her learning about the Nature Valley brand, and (ii) confounding changes in the market environment. Regarding the latter, Nature Valley may have rolled out a new marketing campaign at the same time as the stockout. Or, alternatively, our consumer might have tired of the taste of Sunbelt granola bars so that, even if she had successfully picked up her go-to Sunbelt granola bars, she would still have switched to a new brand afterwards—like Nature Valley.

To isolate the influence of the stockout substitution, I identify a "control consumer" who, like the focal consumer, has never purchased any Nature Valley-branded granola bars before. Additionally, the control consumer has ordered the same Sunbelt Sweet & Salty granola bars as the focal consumer, from the same store, and on the same day. Unlike the focal consumer, however, the control consumer arrives at the store just before the Sunbelt Sweet & Salty granola bars go out of stock. As a result, he does not experience a stockout substitution, so there is no chance that he learns his true tastes for the Nature Valley brand on this trip. Hence, to the extent that he purchases the Nature Valley brand in the future, this solely reflects confounding changes in the purchase environment, *not* learning. This enables me to difference out confounding changes in the purchase environment. Whereas the focal consumer's future purchases reflect both (a) her learning about Nature Valley (due to the substitution) and (b) confounding changes in the environment, the control consumer's future purchases reflect only the latter. Hence, if the focal consumer proceeds to purchase Nature Valley granola bars more often than does her control counterpart, the disparity likely stems from the former consumer's learning.

Having sketched the intuition of my strategy, I will now spell out the specifics. As suggested by the foregoing thought experiment, I begin by identifying stockout substitutions where the consumer has never purchased the substitute's brand before. For each such substitution, I identify all successful curbside pickups of the focal consumer's preferred product *before* it went out of stock.[24] Of these successful pickups, I drop those where the purchaser has bought the substitute's brand before. Among the remaining consumers, the "control consumer" is defined as the *last* one to successfully pick up the ordered product before it goes out of stock.[25] Under the null hypothesis that stockout substitutions do not result in consumer learning, this control consumer's future purchases should resemble those of the focal consumer. In particular, the two consumers should purchase the substitute's brand with similar frequency.

Besides brand, this procedure can also be adapted to study other characteristics. To do so, I first identify stockout substitutions where the substitute's version of the relevant characteristic is one that the consumer has never purchased before, so that she will learn about the substitute's version if she accepts. Then I single out a "control consumer" from among the population of consumers who have ordered the same product as the focal consumer, and who, like the focal consumer, have never purchased a product with the substitute's version of the relevant characteristic. As with brand, I focus on the last such consumer to successfully pick up before the stockout event.

Table 4 presents the results of this descriptive exercise. The results bear an "intent-to-treat" interpretation. That's to say, I do not distinguish between observations where the substitute is accepted (in which case the consumer learns about the substitute) and observations where the substitute is rejected (in which case the consumer does *not* learn). This is because acceptance is endogenous; consumers who expect to like the substitute's observable characteristics are more likely to accept than are consumers who expect to *dislike* its characteristics.

With this in mind, Table 4 is organized as follows. For each observable characteristic (listed in the leftmost column), the second column lists the number of stockout substitutions (i.e., "observations") such that the focal consumer will learn about the substitute's version of the characteristic if she accepts. The remaining columns compare these focal consumers' purchases with those of the control consumers (who do *not* suffer a substitution), before and after the stockout event. Regarding the number of purchases observed before and after the stockout event, I do not distinguish between the focal and control consumers, but rather report the average across both consumer types (who are similar in this respect).

Focus first on consumers' shopping trips before the stockout event. The average consumer has made a substantial number of purchases before the stockout event, ranging from about ten to forty

[24] In Appendix B, I repeat the same procedure for the *first* consumer to pick up after the stockout ends. However, intuition suggests that stockouts may cause endogenous price changes where the store hikes the prices of products that recently went out of stock. By contrast, purchases *before* the stockout are insulated from such endogenous price adjustments. At all events, the results are quantitatively unchanged by this alternative method of selecting the "control consumer;" see Appendix Table 6.

[25] To ensure that the purchase environment is comparable to that experienced by the focal consumer, I drop any observations where the "control consumer" picks up the focal consumer's preferred product on a date prior to the stockout event.

Table 4 – Successful Pickups versus Substitutions That (Might) Result in Learning

Characteristic	Obs.	No. of purchases: Before stockout	No. of purchases: After stockout	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Suffer substitution (Focal group)	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Successful pickup (Control group)
		Panel A. Flavored milk			
Brand	165	23.3	20.0	0.048	0.033
		(37.9)	(26.7)	(0.149)	(0.115)
Pct. milkfat	49	11.6	11.2	0.103	0.096
		(22.5)	(16.3)	(0.240)	(0.168)
Size[a]	47	10.6	14.6	0.173	0.175
		(27.7)	(21.4)	(0.226)	(0.293)
		Panel B. Frozen french fries			
Brand	125	17.3	8.9	0.073	0.065
		(21.5)	(10.4)	(0.175)	(0.206)
Flavor	20	11.8	8.4	0.112	0.141
		(22.3)	(12.1)	(0.183)	(0.275)
Size[a]	23	30.2	10.9	0.009	0.010
		(48.9)	(12.2)	(0.036)	(0.034)
		Panel C. Granola bars			
Brand	60	27.6	16.3	0.052	0.026
		(41.8)	(18.3)	(0.121)	(0.087)
Calories[b]	8	16.8	9.2	0.016	0.116
		(16.2)	(8.7)	(0.042)	(0.195)
Flavor	141	37.1	19.6	0.032	0.021
		(60.1)	(32.0)	(0.108)	(0.077)
No. of bars	9	49.4	21.5	0.048	0.172
		(82.4)	(22.2)	(0.068)	(0.331)
Texture	10	70.2	26.6	0.000	0.046
		(82.5)	(30.9)	(0.000)	(0.145)

Notes: This table presents "intent-to-treat" evidence that stockout substitutions sometimes cause consumers to learn about observable product characteristics. For a given observable characteristic, each observation consists of a stockout substitution where the substitute does not share the relevant characteristic with any of the consumer's past purchases. Thus, if the consumer accepts, she will learn about her tastes for the substitute's version of the relevant characteristic. To capture confounding changes in the environment besides learning—such as advertising or discounts—results are also reported for "control consumers" who resemble the focal consumers in most respects, but who do not experience a stockout event. For a given substitution, the control consumer is drawn from the population of consumers for whom—like the focal consumer—no past purchases share the relevant characteristic with the substitute. Additionally, the control consumer will have ordered the same product as the focal consumer, from the same store, and on the same day. Unlike the focal consumer, however, she will have successfully picked up her preferred product before it went out of stock. From the pool of consumers satisfying the foregoing criteria, I select the last one to have successfully picked up before the stockout event.

[a] Binned (small/medium/large)

[b] Binned (less than 100 cal; between 100 and 200 cal; more than 200 cal)

or so (depending on the product category and characteristic thereof). Recall that, by construction, none of these consumers have ever purchased a product that shares the relevant characteristic with the substitute.[26] Now turn to consumers' purchases after the stockout event. Here, a nonzero fraction of both the focal and control consumers' purchases share the relevant characteristic with the substitute. Moreover, where some characteristics are concerned, perceptible differences emerge between the focal and control consumers. For ease of exposition, I will first discuss these differences in relation to the characteristic of brand (which is common to all three product categories) and then turn to other characteristics. With this in mind, compare the rightmost pair of cells in the top row of each panel. These cells report the fraction of the focal and control consumers' future purchases that share the (hitherto-unfamiliar) brand of the substitute. Notice that the focal consumers—who, due to a stockout substitution, enjoy the opportunity to learn about the substitute's brand—proceed to purchase that brand more frequently than do the "control consumers," who do not learn about it. This disparity in the choice share of the substitute's brand is economically significant. Take the case of granola bars, for example. The focal consumers proceed to purchase the substitute's brand of granola bars twice as often as do their control counterparts; whereas the former purchase the substitute's brand on 5.2% of subsequent shopping trips, the latter only do so on 2.6%. As for flavored milk and frozen french fries, the fraction of future purchases that share the substitute's brand is, respectively, 1.5 and 0.8 percentage points greater for the focal consumers than for their focal counterparts.

Besides brand, it is more difficult to judge whether consumers learn about other observable characteristics. This is because there are comparatively few observations where none of the consumer's past purchases share the relevant (non-brand) characteristic with the substitute. The lone exception to this pattern is the characteristic of flavor within the product category of granola bars (Panel C). Among the 141 stockout substitutions in which the substitute's flavor is unfamiliar to the focal and control consumers, the focal consumers proceed to purchase that flavor 1.1 percentage points more frequently than the control consumers do. Notice that this disparity is smaller than the corresponding one for the characteristic of brand, which suggest that consumers may learn more about their preferences for brands than their preferences for flavors.

There are other mechanisms besides learning that could explain these results. One such mechanism is the "buy it again" feature of the store's app and website, which enables consumers to perform repeat purchases with a single click. Importantly, the "buy-it-again" list includes accepted stockout substitutes. This raises the following question. Do consumers purchase stockout substitutes on subsequent shopping trips because it is convenient, or because they have learned about the substitutes? To adjudicate between these explanations, I modify the foregoing descriptive exercise as follows. Rather than comparing focal and control consumers with respect to all subsequent purchase—both

[26]For the intent is to study consumers who, due to their past purchase histories, are presently unsure of their tastes for the substitute's version of the characteristic.

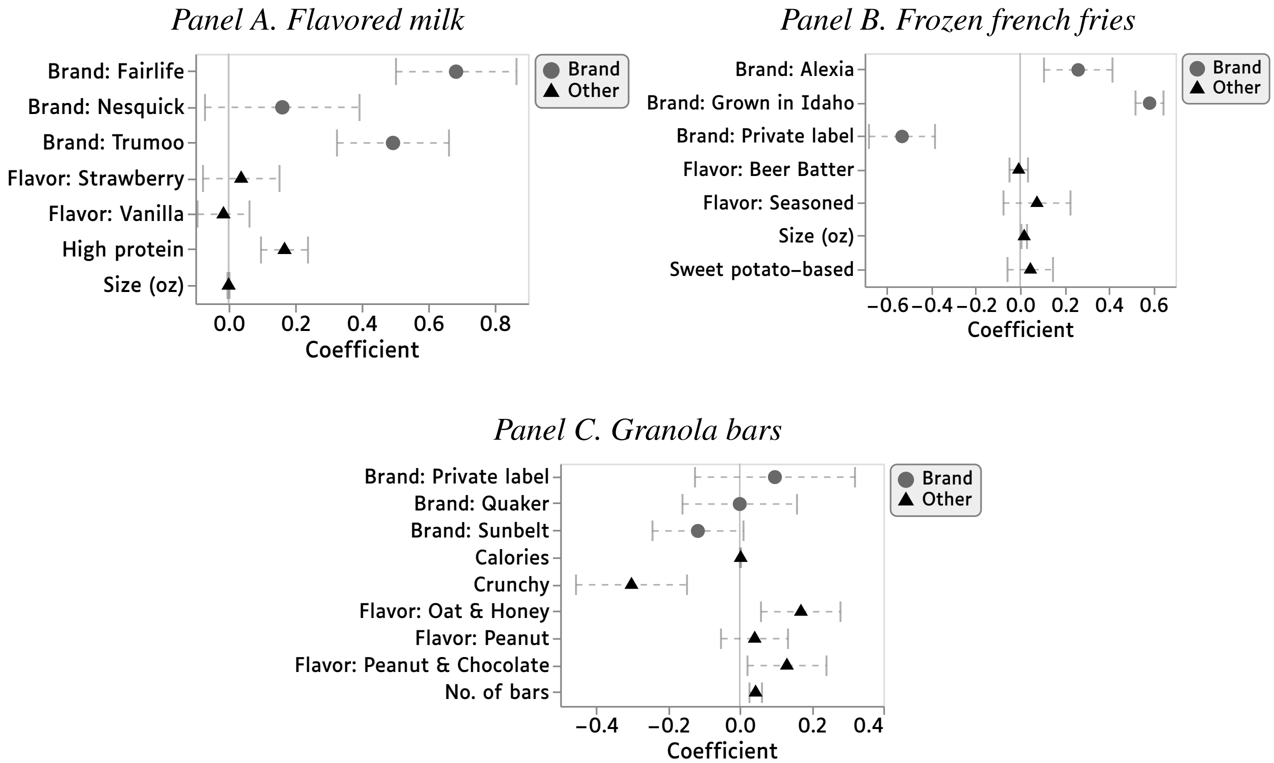

FIGURE 1 – DETERMINANTS OF RETAIL MARGINS

Notes: This figure plots estimates of the coefficients (γ) on products' observable characteristics using the specification in equation (1). The horizontal bars provide 95% confidence intervals.

online and offline—I instead focus solely on in-store purchases, which should be unaffected by the "buy-it-again" list. Reassuringly, the results (which appear in Appendix Table 5) still display a disparity between the focal and control consumers. Specifically, the former purchase the substitute's brand more often on future in-store shopping trips than the latter do. This suggests that the results are not driven by the "buy-it-again" feature of the store's website.

C. *What Determines Products' Retail Margins?*

In this subsection, I study the determinants of products' *retail margins*—that is, the differences between their retail prices and wholesale costs.[27] How do observable characteristics like brand, size, or flavor influence retail margins?

To provide insight, I estimate the linear regressions of the form

$$p_{jts} - wc_{jts} = x_j \gamma + \nu_{jts}, \tag{1}$$

[27] As mentioned previously, the store reported a hybrid cost measure (wholesale cost + some fixed costs) until 2021. For simplicity, these descriptives focus on the time period after 2021, when wholesale costs are directly observed.

where p_{jts} and wc_{jts} respectively denote the price and wholesale cost of good j at time t in store s, while x_j denotes the observable characteristics. As the data span more than seven years, I adjust for inflation by converting both prices and margin costs to 2021 dollars.[28]

Figure 1 reports the results. Each panel plots the estimated coefficients on the observable characteristics of the product category in question (with the horizontal bars providing 95% confidence intervals.) Because the characteristic of brand is relevant to all three product categories, the coefficients on brand dummy variables are depicted as gray circles, whereas the coefficients on other variables are depicted as black triangles. Concerning discrete characteristics with many different values (like brand or flavor), I assign the top-selling value as the base level and then report the coefficients on the three next-most-popular values.

Consider first the coefficients on the brand dummies. These bear the following interpretation: how do the retail margins of a product belonging to the indicated brand differ from those of an otherwise-identical product belonging to the omitted brand (which is the top-selling brand in the category)? The estimates suggest that products' brands are indeed an important determinant of their respective retail margins. With only one exception,[29] there is a predicted disparity of at least \$0.09 in retail margins between otherwise-identical products that belong to different brands within a given category. Now turn to products' non-brand discrete characteristics (such as the dummy on high-protein flavored milks). Regarding flavored milk and frozen french fries, these do not seem to influence retail margins very much; the estimated coefficients are small in absolute value. For granola bars, by contrast, non-brand discrete characteristics do influence margins to a meaningful degree. Most notably, crunchy granola bars afford retail margins that are \$0.30 smaller than those of otherwise-identical chewy granola bars.

It is more difficult to assess the continuous characteristics' influence on retail margins because their coefficients depend on their respective units of measurement. Consider, therefore, the change in the predicted margin when a given continuous characteristic increases by one standard deviation. Regarding flavored milk, increasing the size by one standard deviation (namely, 36.8 fl oz) is associated with an \$0.00 decrease in retail margin. (For reference, the average retail margin is \$0.40.) As for frozen french fries, a one standard deviation increase in size (7.3 oz) is associated with a \$0.13 increase in retail margin (relative to an average margin of \$0.68). And for granola bars, a one standard deviation increase in the number of bars (5.2 bars) is associated with a \$0.23 increase in the retail margin; while a one standard deviation increase in the calories per bar (38.6 calories) is associated with a \$0.11 increase in the retail margin. (The average margin is \$0.64.)

Overall, these regressions indicate that the characteristic of *brand* is among the primary determinants of retail margins in all three product categories.

[28] To reduce the influence of brief fluctuations in the CPI, I normalize values using the six-month smoothed CPI.

[29] The Nature Valley and Quaker brands of granola bars, whose retail margins are essentially indistinguishable.

4. Conceptual Model

This section presents a conceptual model of orders and stockout substitutions in curbside pickup. The goal is to highlight the trade-offs faced by the store as it chooses a stockout substitute. On the one hand, the store would like to steer the consumer's learning by offering her a substitute from a high-margin brand that she has never tried before. If she accepts, she may learn that she likes this brand and then purchase its (profitable) products in the future. On the other hand, the store wants to maximize the probability of the substitute's being accepted, as well as the probability that the consumer is happy with the store's handling of the stockout (so that she does not reduce her future patronage).[30] And the latter objectives are likelier to be achieved if the store instead offers a substitute from a familiar, albeit lower-margin, brand.

Consider a store that offers three goods for curbside pickup: A, A', and B. Let p_j and mc_j denote the price and marginal cost, respectively, of good $j \in \{A, A', B\}$. Assume that good B affords a higher retail margin than do goods A and A':

$$p_B - mc_B > \max\{p_A - mc_A, p_{A'} - mc_{A'}\}.$$

The store serves a consumer who makes two shopping trips, indexed by $t \in \{1, 2\}$. On each trip, she either (i) purchases one of the three "inside goods" sold by the store; or (ii) chooses the "outside option" of no purchase, indexed by $j = 0$. Importantly, she possesses incomplete information about her preferences among the three goods. Whereas she knows her tastes for goods A and A' from prior purchase experiences, she does not know her taste for good B. However, she expects to like good B less than goods A and A'.

Suppose that our consumer orders good A on trip 1. However, A later goes out of stock and the store needs to choose a substitute. Should it offer A' or B? The optimal choice of substitute depends on four criteria. Two of these criteria concern the store's margins on trip 1. These include (a) the potential substitute's retail margin and (b) the probability of acceptance. Regarding (b), our consumer will accept a substitute $s \in \{A', B\}$ if, and only if, she expects to prefer it to the "outside option" of no purchase (that is, "good 0").[31]

The store's choice of substitute also affects its future profits. In particular, the choice of substitute may influence (c) the probability that the consumer returns for a second shopping trip and (d) her purchase conditional on doing so. Concerning (c), the consumer is more likely to choose the outside option on trip 2—thereby leaving the store with no retail margin—if she is unhappy with the offered

[30] She might do so out of annoyance with the store, or in expectation that its rivals will better handle stockout substitutions.

[31] Here, I implicitly assume that the consumer is myopic, meaning that she overlooks the (expected) value of learning her true tastes for good B. In Section 5A, I explain why this assumption is likely to provide a close approximation of consumers' true behavior in the context of curbside grocery pickup.

substitute. As for (d), if the store offers good B as the substitute, the consumer may discover that she likes the good more than she had expected and, in consequence, purchase it on her second trip. Because good B affords greater retail margins than goods A or A', this would boost the store's future profits.

In view of the foregoing criteria, the store's optimal choice of substitute can be formalized as follows. Let δ denote the discount factor for profits on trip 2. Then, given that the consumer originally ordered good A, the optimal substitute is:

$$s^\star(A; p, mc) \equiv \underset{s\in\{A',B\}}{\arg\max} \Big\{ \Pr[\text{accept } s]\Big(p_s - mc_s + \delta\, \mathrm{E}[\Pi_2 \mid \text{accept } s]\Big) + \big(1 - \Pr[\text{accept } s]\big) \cdot \Big(0 + \delta\, \mathrm{E}[\Pi_2 \mid \text{reject } s]\Big)\Big\}. \tag{2}$$

In this equation, $\Pr[\text{accept } s]$ denotes the probability that the consumer accepts s, given that she originally ordered good A.[32] As for $\mathrm{E}[\Pi_2 \mid \text{accept } s]$, this term measures the store's expected profits on the second trip, given that she originally ordered A and then accepted s as a substitute. It can be decomposed as

$$\mathrm{E}[\Pi_2 \mid \text{accept } s] = \sum_{j\in\{0,A,A',B\}} (p_j - mc_j) \Pr[\text{order } j \text{ on trip 2} \mid \text{accepted } s \text{ as substitute}].$$

Notice that the conditional order probabilities on trip 2 depend on the identity of the substitute that was accepted on trip 1. If the substitute was A', the consumer will not have learned anything from the stockout substitution (as she already knew her taste for A'). Hence, she will probably order good A on trip 2, just as she did on trip 1. But if the substitute was B, the consumer may well have learned that she prefers B to A. That's to say,

$$\Pr[\text{order } B \text{ on trip 2} \mid \text{accepted } \boldsymbol{B} \text{ as substitute}] \geqslant \Pr[\text{order } B \text{ on trip 2} \mid \text{accepted } \boldsymbol{A'} \text{ as substitute}].$$

5. Empirical Model and Estimation

In this section, I build a learning model of demand for differentiated products. Then I describe the estimation procedure.

[32]Throughout equation (2), my notation suppresses the dependence on the consumer's original order choice.

A. *The Model*

Consider discrete choice among J_t goods/products at "time" t,[33] indexed by $j \in \mathcal{J}_t \equiv \{1, \ldots, J_t\}$. These goods are sold under differentiated brands b (such as "Sunbelt" or "Nature Valley"). Let $B(j)$ denote the brand of good j.[34]

The utility that consumer i derives from good j depends partly on her liking (or "taste") for its brand. This is measured by the scalar $v_{iB(j)} \in \mathbb{R}$. Brand aside, utility also depends on the good's non-brand observable characteristics (x_j), its price (p_{jt}), an unobserved demand factor (ξ_{jt}),[35] and an i.i.d. Gumbel error (ε_{ijt}). In all,

$$u_{ijt} = v_{iB(j)} + x_j\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}. \tag{3}$$

Of course, the consumer is not obliged to purchase any of the J_t goods on offer. Let $j = 0$ index the "outside option" of purchasing nothing (which provides utility u_{i0t}).[36]

Learning.—Consumers can, in principle, learn about their tastes for any observable characteristic. However, computational limitations force me to focus on just one characteristic. I choose the characteristic of *brand* for two reasons. First, descriptive evidence suggests that consumers learn more about their tastes for brands than about their tastes for other characteristics (see Section 3B). And second, the characteristic of brand is among the primary determinants of products' retail margins (see Section 3C). Hence, the store may profit more from steering consumers' learning about brands than from steering their learning about other characteristics.

I model consumers' learning about brands as follows. If consumer i has never purchased brand b, she holds the following (unbiased) beliefs about her tastes for the brand:

$$v_{ib} \sim \text{Normal}\left(\mu_{ib}, \iota_b^2\right). \tag{4}$$

Once she purchases one of the brand's products (that is, some good j such that $B(j) = b$), she will learn her true tastes v_{ib} for the brand. Specifically, v_{ib} will be randomly drawn from equation (4), with the results of the draw determining her tastes for the brand on all future trips.[37]

[33] In point of fact, t is defined as the combination of a specific store location and time. For expositional simplicity, I focus on the temporal dimension of the index.

[34] Formally, the function $B : \bigcup_{t\in\mathcal{T}} \mathcal{J}_t \to \mathcal{B}$ maps from each good sold to its brand. (Here $\mathcal{T} \equiv \{1, \ldots, T\}$ denotes the set of all time periods, while $\mathcal{B}$ denotes the set of all brands.)

[35] This term captures unobserved store-level promotional activities that temporarily shift demand for the good, such as being featured in a flyer or being placed in a prominent location (i.e.,"endcap").

[36] I normalize $u_{i0t} = \varepsilon_{i0t}$, where ε_{i0t} is an i.i.d. Gumbel error.

[37] Here, I implicitly assume that a single consumption experience suffices to obtain full knowledge of one's true tastes for a brand. Although this "one-shot" model of learning is more restrictive than the Bayesian one used in much of the literature (e.g., Erdem and Keane [1996]), it affords two key advantages. First, it accommodates richer heterogeneity in consumers' underlying tastes than would a more complex model of learning (see Erdem, Keane, and Sun [2008] or Che, Erdem, and Öncü [2015]). And second, "one-shot" learning is likely a close approximation of consumers' true learning

Consumers hold heterogeneous prior beliefs about their tastes for a given brand. In particular, prior expected tastes for brands (the μ_{ib}'s) are normally distributed across the population of consumers, with

$$\mu_{ib} \sim \text{Normal}\left(\mu_b, \sigma_b^2\right)$$

for each brand b. However, all consumers' priors are equally informative about a given brand b (hence the absence of an i subscript on ι_b^2 in equation [4]).

In-Store Purchases, Curbside Orders, and Stockout Substitutions.— Whether she is shopping in-store or online, each consumer i purchases one unit of the good with the highest expected utility.[38] The source of uncertainty is her tastes for brands. Concerning goods j whose brands $B(j)$ she has never purchased before, the consumer's expected utility depends on her prior-expected tastes for its brand, namely $\mu_{iB(j)}$. As for goods j whose brands she *has* bought before, she knows their exact utilities (u_{ijt}) because she has already learned her true brand tastes ($\nu_{iB(j)}$) from experience.

Let $\mathcal{I}_{it}$ denote the information set held by consumer i at time t. Regarding each brand b that the consumer has *not* yet purchased, the information set contains the parameters μ_{ib} and ι_b^2 that characterize her prior beliefs. As to a brand b that she *has* previously purchased, $\mathcal{I}_{it}$ contains her true tastes ν_{ib}.

The expected utility of good $j \in \mathcal{J}_t \setminus \{0\}$ is given by

$$\mathrm{E}[u_{ijt} \mid \mathcal{I}_{it}] = \mathrm{E}[\nu_{iB(j)} \mid \mathcal{I}_{it}] + x_j\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt},$$

with

$$\mathrm{E}[\nu_{iB(j)} \mid \mathcal{I}_{it}] = \begin{cases} \nu_{iB(j)} & \text{if } i \text{ has bought brand } B(j) \text{ before} \\ \mu_{iB(j)} & \text{otherwise.} \end{cases} \tag{5}$$

If the consumer is placing an order for curbside pickup, her preferred good—say, $j^\star$—may go out of stock. She will then be offered a substitute $s \in \mathcal{J}_t \setminus \{0, j^\star\}$, which she will accept if and only if

$$\mathrm{E}[u_{ist} \mid \mathcal{I}_{it}] \geqslant u_{i0t}. \tag{6}$$

Are Consumers Myopic or Forward-Looking?—Consumers' purchases affect their expected utility on future shopping trips as well as on the present one. The same is true of their decisions to accept or reject stockout substitutes. This is because consumers can learn their true tastes for a brand by either purchasing one of its products or by accepting one of them as a substitute. The resultant learning

process in this environment. (Intuitively, less experience is required to learn whether one likes a packaged snack or drink than whether one likes a more complex good, such as a car or a computer.)

[38] I do not model the decision to order a good in the first place. In the data, it is difficult to distinguish between curbside orders where (i) the consumer considered ordering a product from the relevant differentiated-products market, but decided against it; and (ii) the consumer never considered ordering anything from the market in the first place.

would enable them to make more informed—and, in expectation, higher-utility—purchases in the future.

Are consumers forward-looking, meaning that they account for the (expected) value of learning? Or are they myopic, meaning that they do not? I assume the latter for two reasons. The first concerns the purchase environment. When shopping for groceries, consumers typically face a multitude of low-stakes decisions. To reduce the cognitive burden, consumers may focus on their present-trip utility, rather than solving the dynamic maximization problem induced by learning's impact on future utility. Behavioral considerations aside, it is also computationally useful to assume that consumers are myopic. In prior work where consumers are *not* assumed to be myopic, but rather forward-looking, it has usually proved necessary to assume that all consumers share the same underlying preferences among brands.[39] By assuming that consumers are myopic, I can accommodate heterogeneous underlying tastes for brands. And, in terms of forecasting consumers' behavior under counterfactual substitution policies—the ultimate goal of this study—it is arguably more important to capture heterogeneity in consumers' underlying brand tastes than to model (potentially) forward-looking behavior.[40]

B. Estimation Method

Several sets of parameters need to be estimated. The first set of parameters pertain to consumers' *prior expected* tastes μ_{ib} for brands b, as well as their *true* tastes v_{ib}. Regarding the latter, two distinct parameters contribute to heterogeneity in consumers true tastes v_{ib} for a given brand b. One is σ_b^2, which measures heterogeneity in consumers' prior expected tastes for the brand; while the other is ι_b^2, which gauges the amount of learning when consumers first try the brand. Summing these two parameters yields the standard deviation of consumers' true tastes for a given brand. Specifically,

$$v_{ib} \sim \text{Normal}(\mu_b, \sigma_b^2 + \iota_b^2).$$

This follows immediately from $v_{ib} \sim \text{Normal}(\mu_{ib}, \iota_b^2)$ and $\mu_{ib} \sim \text{Normal}(\mu_b, \sigma_b^2)$. For further details on the brand parameters, see Appendix C.

The second set of parameters bears on products' non-brand observable characteristics x_j. Let k index specific = characteristics such that $x_j = (x_{j1}, \ldots, x_{jk}, \ldots, x_{jK})$ for each good j. Because consumers innately know their tastes β_{ik} for each non-brand characteristic k, the distribution of

[39] Osborne (2011) and Shin, Misra, and Horsky (2012) provide noteworthy exceptions. Both assume that consumers are forward-looking and that they possess heterogeneous underlying preferences. To surmount the resultant computational challenges, however, both studies resort to smaller estimation sample sizes (fewer than 700 households) than would be ideal for this study, where heterogeneity in consumers' past purchase histories is of direct interest.

[40] Concerning the Norwegian market for new books, Daljord (2022) provides quasi-experimental evidence that consumers evince far greater impatience than the real rate of interest would imply. So, to the extent that consumers are forward-looking while shopping for groceries—arguably, a faster-paced activity (with lower stakes per item purchased) than that of shopping for new books—this feature of their behavior is likely of second-order importance.

consumers' taste parameters is recovered with the same procedure as in the familiar mixed logit model (see Arteaga et al. [2022]). For computational tractability, I cannot estimate random coefficients on all non-brand characteristics. Rather, for most non-brand characteristics k, I estimate fixed coefficients such that $\beta_{ik} = \beta_k$ for all consumers i. As for the remaining non-brand characteristics, I assume that tastes β_{ik} are normally distributed across the population of consumers, with

$$\beta_{ik} \sim \text{Normal}(\beta_k, \sigma_k^2).$$

I assign the random coefficients within a given product category based on the extent of *within-brand* variation in characteristics. For, when brands specialize in specific versions of a given characteristic, it is difficult to untangle consumers' tastes for the characteristic from their tastes/learning with respect to brands.

The third set of parameters governs consumers' price sensitivity. I assume that the random price coefficient α_i follows a truncated normal distribution with shift parameter α, scale parameter σ_α^2, and one-sided truncation of the left tail so that the support is $(0, \infty)$.

The fourth set of parameters concerns the method by which consumers accept or reject stockout substitutes. Before September 2021, consumers learned of stockouts upon arriving at the store and then accepted or rejected the substitute on the spot. Since September 2021, however, consumers have been able to accept or reject remotely using the store's app or website. Because this new procedure may have lowered the cost of rejecting a substitute,[41] I allow the utility of rejection to differ before versus after September 2021. In particular, I assume that the consumer will accept a substitute s if and only if

$$\mathrm{E}[u_{ist} \mid \mathcal{I}_{it}] \geqslant u_{i0t} - \gamma \cdot 1[\text{reject in-person}], \tag{7}$$

where the parameter γ gauges the added cost of rejecting a substitute in-person (as opposed to remotely).

All the foregoing determinants of demand are observed in the data. However, demand also depends on unobservable factors that vary across space and time. One such factor is store- and time-specific promotional activities, like inclusion in a flyer or placement in a prominent location (a.k.a. "endcap"). In the utility specification, shocks of this description are represented by the term ξ_{jt}.[42] To recover ξ_{jt}, I employ the control function approach proposed by Kim and Petrin (2019). This approach proceeds in two steps. In the first, I estimate the reduced-form pricing function. Besides the variables that enter the utility function—namely, the brand $B(j)$ and the non-brand observable characteristics x_j—the

[41] For a start, it may be easier for the consumer to plan a trip to an additional grocery or convenience store if she knows of the stockout in advance. There may also be a psychological dimension; when accepting or rejecting substitutes in-person, consumers might feel social pressure to accept the substitute.

[42] Recall that t indexes the combination of specific store locations and times (although, for expositional reasons, I have hitherto focused primarily on the latter dimension.)

pricing function also incorporates a set of instrumental variables that are excluded from demand. I employ products' wholesale costs wc_{jt} as the excluded instruments. The intuition is that wholesale costs should be correlated with retail prices, but uncorrelated with store-level promotional activities. All told, the reduced-form pricing function takes the following form:

$$p_{jt} = \eta_{B(j)} + x_j \varphi + \psi \cdot wc_{jt} + \tilde{\xi}_{jt}.$$

I estimate this equation via OLS. Because the store changed its internal cost measure in January 2021,[43] I perform separate regressions before and after that date. Then, in the second step of the control function procedure, I substitute $\xi_{jt} = \lambda \tilde{\xi}_{jt}$ in the utility function. Here, $\tilde{\xi}_{jt}$ is the residual from the reduced-form price regression and λ is a parameter to be estimated. Due to the change in the store's internal cost measure during January 2021, I estimate separate coefficients $\lambda_{\text{pre-21}}$ and $\lambda_{\text{post-21}}$ on the control functions before and after that date.

With the control function in hand, the parameters that govern consumers' utility and learning are obtained via maximum simulated likelihood estimation. My estimation code is adapted from Arteaga et al. (2022). See Appendix C for details on the estimation method.

Identification.—Formal identification of the model's parameters is beyond the scope of this paper. Instead, I will describe how the parameter estimates depend on specific moments of the data. Because previous work has already identified differentiated products demand in the absence of consumer learning (see Berry and Haile [2024, 2021, 2016, 2014]), as well as random-coefficients discrete choice more generally (see Fox et al. [2012] and Iaria and Wang [2024]), my discussion focuses on the parameters that pertain to consumers' learning.[44]

First consider μ_b. This parameter measures how much the average consumer expects to like brand b before she tries it. Because consumers' prior beliefs are assumed to be unbiased, μ_b also gauges how much the average consumer would *actually* like the brand if she tried it.[45] The parameter μ_b is sensitive to the following moment of the data. Are brand b's product's more or less popular than would be expected, given their respective (non-brand) observable characteristics, prices, and unobserved demand factors? If they are more popular than expected, brand b must be comparatively well liked. Thus, μ_b should be large. On the other hand, if the brand's products possess smaller market shares than expected, consumers must not like the brand very much. Hence, μ_b should be small.

Now turn to σ_b^2, which measures heterogeneity in expected tastes for brand b among consumers

[43] Before January 2021, the store included some fixed costs in its internal cost measure (as well as the wholesale cost).

[44] Although Shin, Misra, and Horsky (2012) identify a Bayesian learning model of demand, the intuition differs from the "one-shot" learning model estimated here. In a Bayesian learning model, the researcher must untangle two distinct learning effects: *bias reduction* and *uncertainty reduction*. In a one-shot model, by contrast, a single consumption experience suffices to eliminate both bias and uncertainty in the consumer's beliefs.

[45] This is because consumers' prior beliefs are assumed to be biased.

who have not yet tried the brand. This parameter is sensitive to variation across consumers in the number of shopping trips *before* they purchase the brand for the first time. To see the intuition, suppose first that there is little variation in how long consumers wait before trying one of the brand's products. This suggests that consumers are similarly optimistic about their tastes for the brand, so σ_b^2 is likely small. Now imagine, instead, that there is considerable variation in how long consumers wait before trying the brand; whereas some consumers purchase the brand on one of their earliest shopping trips, others wait a long time before doing so. These two groups of consumers probably differ in their expected tastes for the brand, with the former group being more optimistic than the latter. Thus, σ_b^2 should be large.

Finally, consider ι_b^2. This parameter measures the amount of learning that consumers experience when they try one of brand b's products for the first time. To what extent do their true tastes for the brand (ν_{ib}) differ from their expected tastes (μ_{ib})? This parameter partly depends on the following moment of the data.[46] Consider the subset of consumers who try brand b for the first time because of a stockout substitution. How often do these consumers purchase brand b in the future? If they seldom do so, they probably did not learn much about the brand from the substitution. Rather, the experience confirmed their pessimistic prior beliefs about their tastes for the brand. Consequently, ι_b^2 should be small. Now suppose, instead, that many consumers proceed to purchase brand b quite frequently. These consumers likely learned a lot from the substitution, finding brand b more to their tastes than they had expected. Hence, ι_b^2 should be large.

C. *Construction of Estimation Data Set*

In this subsection, I describe how I assemble the data set used to estimate the demand model above. As the procedure closely resembles the one used by Zeyveld (2024), much of this subsection is adapted from Section 6 of that paper.

I cannot estimate demand for all the products within a given product category due to computational constraints. For this reason, I exclude slow-selling brands and products from estimation.[47] Computational constraints also prevent me from including all consumers in estimation. Rather, within each product category, I perform estimation on the following subset of consumers. First, I find consumers

[46] In addition to variation from stockout substitutions, the ι_b^2 estimates also depend on a subtler relationship between (i) the number of purchases before consumers first try out the brand, and (ii) the frequency with which they purchase the brand's products thereafter.

[47] Regarding flavored milk, I estimate demand for products that are (i) sold under one of the top three brands and (ii) command at least 0.5% market share among consumers who have experienced at least one stockout substitution. (These products compose 88.9% of purchases by the consumers whose data are ultimately used in estimation.) As for frozen french fries, I estimate demand for products that are (i) sold under one of the top two brands and (ii) command at least 1% market share among consumers with 1+ substitutions. (Such products constitute 72.4% of purchases by consumers whose data are used in estimation.) Finally, concerning granola bars, I estimate demand for products with >1% market share among consumers with 1+ substitutions. (Such products represent 36.8% of estimation consumers' purchases.)

who experience stockout substitutions where both the out-of-stock product and the substitute are popular products. (These consumers are used both in estimation and in counterfactuals.) Next, to increase the sample size, I randomly sample additional consumers who have also experienced a stockout substitution—albeit one where either the ordered product or the out-of-stock one is a slow-selling product. (These consumers are included for estimation but excluded from counterfactuals.)

Having sampled consumers for estimation, I need to reconstruct the discrete choice problems that they faced on each shopping trip. What products were available for purchase? And what were their prices? Recall that the scanner data directly record the UPC and price of the item that was purchased. However, these data also enable me to infer the UPCs and prices of goods that the consumer did *not* purchase. To do so, I consult the chain's product catalog in order to obtain the UPCs of the store's offerings within the relevant category. Then, turning to the scanner data, I compare these UPCs with those of products sold at the relevant store. If I observe a given product being purchased at the relevant store on the same day as our consumer's shopping trip, I assume that the product was within her choice menu. Failing that, I presume that the product was available if it was purchased on both the day before *and* the day after our consumer's trip. Otherwise, I assume that the product was absent from the consumer's choice set (either because it was out of stock, or because the store did not carry it at all).

Given that a product appears to be available, I impute its price as being the mean purchase price on the day of the consumer's shopping trip (within the relevant store location).[48] If no purchases are observed on the precise day of the trip, I instead take the unweighted average of the mean purchase prices on the days immediately before and after.

Consumers' purchases sometimes deviate from the underlying assumptions of my discrete choice model. For a start, consumers sometimes purchase multiple distinct products on a single shopping trip. To illustrate, a consumer shopping for granola bars might purchase both Sunbelt and Nature Valley granola bars on the same trip. I drop all such observations from estimation.[49] Furthermore, consumers sometimes purchase multiple units of the same product. For instance, someone might stockpile multiple packages of the same Nature Valley granola bars. In the interest of simplicity, I abstract from the consumer's choice of quantity, focusing only on the choice of product.[50]

Initial Conditions Problem.—Some consumers have made purchases at the store before the earliest date recorded in my data (April 24, 2016). This creates an initial conditions problem. When I observe consumers' purchases early in the data, are they experiencing brands for the first time? Or had they purchased them previously, before coverage begins in the data?[51]

[48] The chain maintains a policy of uniform prices online and in-store.

[49] This results in the exclusion of 54.3% of transactions involving granola bars. As for flavored milk and frozen french fries, 11.5% and 21.6% of transactions are dropped on these grounds, respectively.

[50] In the product categories of flavored milk, frozen french fries, and granola bars, consumers with 1+ stockout substitutions purchase multiple units of a single product on 18.9%, 14.7%, and 22.5% of shopping trips, respectively.

[51] A related, but distinct, concerns purchases at *other* supercenter chains. If someone purchases a given brand for the

In order to minimize this problem, I drop consumers' first nine purchases of flavored milk and french fries, as well as their first six purchases of granola bars. This "burn-in" period is motivated by the following stylized facts. After her first nine shopping trips, three-quarters of flavored milk (frozen french fry) buyers have purchased two-thirds (all) of the brands that they will *ever* buy at the store. Likewise, following their first six shopping trips, three-quarters of granola bar buyers have purchased two-thirds of the brands that they will *ever* buy at the store.

6. Estimation Results

In this section, I report estimates for the demand model developed in Section 5. For readability, I will concentrate on the product category of granola bars. Results for the other product categories—namely, flavored milk and frozen french fries—are relegated to Appendix D, although I will briefly summarize my findings below.

Table 5 presents the demand estimates for granola bars. Focus first on the parameters pertaining to brands (Panel A). Regarding the μ_b estimates, consumers strongly prefer the mainstream brands—namely, Nature Valley and Quaker—to the budget-oriented Sunbelt brand. As for the σ_b^2 estimates, consumers display greater heterogeneity in their prior expected tastes for the mainstream brands than in their prior expected tastes for Sunbelt. Finally, with respect to the ι_b^2 estimates, consumers' prior beliefs about the mainstream brands are far more informative than are their prior beliefs about Sunbelt. In fact, ι_{Sunbelt}^2 exceeds the difference in consumers' mean tastes for the budget and mainstream brands. This suggests that, upon trying Sunbelt for the first time, many consumers find that they prefer it to the mainstream brands (though many other consumers discover that they dislike Sunbelt even more than they had expected).

Now consider products' non-brand observable characteristics. Recall that I do not attempt to model heterogeneity in consumers' preferences for most of these characteristics k. Rather, I recover a fixed coefficient β_k that measures consumers' mean tastes for characteristic k. The sole exception is the dummy variable for chocolate flavoring. There, I estimate normally-distributed heterogeneity in consumers' tastes.

The results in Table 5, Panel B indicate that consumers' utility is increasing in the number of granola bars contained in the package, as well as in the calories per bar. With respect to texture, consumers tend to prefer chewy granola bars to crunchy-textured ones. As for flavor, the average consumer prefers chocolate-flavored granola bars to ones that are not chocolate flavored (such as oats and honey). However, there is substantial heterogeneity around this mean; many consumers prefer

first time at another chain, then her earliest purchase of that brand within the data would not occasion learning. However, most of the behavioral markers that identify the brand parameters are spread over many transactions. This should reduce the bias from the misattribution of learning.

Table 5 – Parameter Estimates for Demand Model
(Product Category: Granola Bars)

	Panel A. Brands		
Variable	Mean expected tastes (μ_b's)	Heterogeneity of expected tastes (σ_b^2's)	Amount of learning (ι_b^2's)
Nature Valley	2.808	2.545	0.134
	(0.082)	(0.034)	(0.017)
Quaker	3.036	2.966	0.790
	(0.079)	(0.030)	(0.019)
Sunbelt	−0.536	1.608	6.037
	(0.090)	(0.046)	(0.058)
	Panel B. Non-brand observables and prices		
	Means (β's or α)	Standard deviations (σ_β^2's or σ_α^2)	
No. bars	0.239		
	(0.003)		
Calories	0.009		
	(0.000)		
Crunchy	−0.297		
	(0.020)		
Chocolate-flavored	1.396	2.484	
	(0.017)	(0.024)	
Price[a]	0.846	0.881	
	(0.017)	(0.014)	
	Panel C. Other explanatory variables		
	Coefficients (λ's or γ)		
Control function (pre-2021)[b]	0.387		
	(0.023)		
Control function (post-2021)[b]	0.725		
	(0.026)		
Reject in-person[c]	2.324		
	(0.123)		

Notes: estimates are based on 78,952 randomly-sampled observations, which involve 4096 households. Of these observations, 2725 are decisions to accept or reject stockout substitutes. Although standard errors are computed with the Halbert/White "robust" correction, they do not account for measurement error in the control function. (This measurement error should be neligible, however, as the control function is based on residuals of OLS regression with millions of store-product-time observations and only a handful of explanatory variables.)

[a] The distribution of price coefficients is assumed to be truncated normal, with support $(0, \infty)$.

[b] The demand shocks are specified as $\xi_{jt} = \lambda \tilde{\xi}_{jt}$, where $\tilde{\xi}_{jt}$ is the residual from the pricing function and λ is a scaling parameter (reported here). This control function is computed separately before/after January 2021, due to a change in the store's internal cost measure.

[c] Until September 2021, consumers accepted or rejected stockout substitutes upon arrival at the store. Beginning September 2021, they could accept or reject substitutes remotely (using the store's app or website).

other flavors to chocolate.

Turn next to the random price coefficient. Recall that α_i follows a truncated normal distribution, with shift parameter α, scale parameter σ_α^2, and one-sided truncation of the left tail so that the support is $(0, \infty)$.[52] Notice that the estimated scale parameter (σ_α) greatly exceeds the estimated shift parameter (α). This suggests that consumers vary dramatically in their price sensitivity.

Finally, consider the coefficients ($\lambda_{\text{pre-21}}, \lambda_{\text{post-21}}$) on the control function,[53] as well as the coefficient γ on the indicator for rejecting stockout substitutes in-person. Regarding the former, the positive (and statistically significant) estimates suggest that consumers' purchases are indeed influenced by unobservable store-level promotional activities (such as products' being placed in prominent locations or highlighted in flyers). As for the latter, recall that consumers have been able to accept or reject substitutes remotely since September 2021 (using the store's app or website). This should, intuitively, reduce the cost of rejecting a substitute. In keeping with this intuition, the estimated coefficient is positive on the interaction between (i) the "outside option" and (ii) a stockout's occurring after September 2021.

Flavored Milk and Frozen French Fries.—The parameter estimates for the categories of flavored milk and frozen french fries appear in Appendix Tables 7 and 8, respectively. The estimates suggest that consumers learn less about flavored milk than they do about granola bars. As for frozen french fries, consumers learn very little. Rather, their prior expected tastes for brands are virtually indistinguishable from their true tastes.

These results suggest that there may be less scope for the store to steer consumers' learning about flavored milk or frozen french fries compared to granola bars.

7. Counterfactual Simulations

In this section, I use my demand estimates to quantify the trade-offs faced by the store as it selects stockout substitutes. As in Section 6, my discussion concentrates primarily on the product category of granola bars.

The store's present policy—hereafter, the "baseline"—aims to provide the closest available substitute for the out-of-stock product. In practice, the choice of substitute is delegated to the worker who is collecting the curbside order. Specifically, the store asks him to use his "best judgement" to choose a suitable replacement for the out-of-stock product. This policy affords two key advantages. First, because the substitute closely resembles the consumer's preferred product, she will probably accept it. The store is, therefore, likely to earn the substitute's retail margin. And second, the consumer

[52] Recall that the price enters the utility function negatively; see equation (3).

[53] As explained in Section 5B, the store's internal cost measured changed in January 2021. I therefore estimate separate control functions before and after that date.

will probably feel satisfied with the store's handling of the stockout. This means that the stockout substitution is unlikely to result in the consumer's reducing her future patronage of the store (see Section 4).

However, the baseline policy neglects two other ways that the store's choice of substitute impacts profits. These include: (i) the substitute's retail margins and (ii) its potential influence on the consumer's learning. Regarding (i), provided that the substitute is accepted, the store's present-trip profits are increasing in its retail margin. As for (ii), if the consumer does not yet know her taste for the substitute's brand, she will learn this if she accepts. This learning may, in turn, influence her subsequent purchases and (by extension) the store's future profits.

To what extent, if any, could the store increase its profits by attending to these additional factors? In taking up this question, I face the following empirical obstacle: it's impossible to quantify the extent to which the store's handling of stockout substitutions influences consumers' future patronage of the store. This is because I only observe consumers' shopping at stores within the chain that provides my data, not their shopping at rival chains. I cannot, therefore, model consumers' choice of grocery store. In principle, I could still try to supply descriptive evidence of substitutions' influence on consumers' expenditures at the store. For instance, I could compare consumers' expenditures during the month before a stockout substitution with their expenditures during the month after. But descriptive analysis of this kind is uninformative for the following reason: Conditional on experiencing a stockout substitution in one of the three product categories studied (flavored milk, frozen french fries, and granola bars), a consumer experiences an average of three or more substitutions in other product categories on the same trip.[54] And when a consumer experiences multiple stockout substitutions on the same trip, I cannot untangle the influence of the focal-category substitution from the influence of the substitutions in other product categories.

The store's handling of stockout substitutions is not, however, a first-order determinant of where consumers shop. Other factors, such as the convenience of the store's location or consumers' liking for the products carried by the store, play a far larger role. Accordingly, my counterfactual simulations take as given that the store's choice of substitute will not affect attrition. I believe that this assumption is unlikely to materially influence the results; if there exists a relationship exists between stockout substitutions and attrition, it is probably of negligible magnitude.[55] Moreover, if the store still worried that steering consumers' learning would increase attrition, it could offer the affected consumers a "substitution discount." This discount could be set at an amount smaller than the expected gains from

[54]Specifically, flavored milk buyers experience an average of 3.48 stockout substitutions in other categories. The corresponding averages for frozen french fries and granola bars are 4.07 and 3.68, respectively.

[55]My counterfactual simulations compare the present-discounted value of expected profits under two stockout policies: (i) the store's existing "baseline" policy, and (ii) a conditionally optimal policy that maximizes expected profits (given that attrition remains constant). The latter policy is unlikely to prescribe excessively distant substitutes from the out-of-stock product, as this would result in an unprofitably high probability of rejection by the consumer.

steering their learning.

With this in mind, the counterfactual simulations proceed as follows. First, I characterize a "steering" substitution policy, which is designed to maximize the store's present-discounted value of expected profits.[56] Here, I only leverage information that is available to the store at the time of the stockout substitution—that is, data from shopping trips *before* the stockout event. Then, in the second step, I compare the present-discounted value of expected profits under the "steering" policy with that under the "baseline" policy. There, I leverage the entirety of the data.

A. Simulation Method

Characterizing the Steering Substitution Policy.—Under the "steering" policy, the store will offer the substitute that maximizes the present-discounted value of expected profits. This depends on three factors: the retail margin of the substitute, the probability of acceptance, and the present-discounted value of expected future profits. Whereas the retail margin is directly observed in the data, the other factors must be simulated.

Focus first on the probability of acceptance. I assume that the store will leverage its knowledge of the consumer's prior purchases as it computes this probability. Intuitively, the consumer should be likelier to accept the substitute if it resembles products that she has previously purchased. This intuition is operationalized as follows. Rather than assigning equal weights to all the simulation draws of the random coefficients, I instead compute "conditional weights" that reflect the consumer's choices up to, and including, her decision to order the out-of-stock product. (See Train [2009]).

Now turn to future profits. How might a consumer's acceptance (or rejection) of a substitute influence the store's expected future profits? In principle, the influence of a stockout substitution might extend infinitely into the future. To avoid overstating the returns to steering consumers' learning, I focus on a short time horizon: one year.

The store faces several sources of uncertainty where future profits are concerned. One is the timing of consumers' future shopping trips. Here, I assume that the store adopts a simple heuristic: for each consumer i, the frequency of future shopping trips is imputed as being the average frequency of her shopping trips up to (and including) the stockout substitution. The store is also unsure of the future availabilities, prices, and wholesale costs of products within the relevant category. For simplicity, I assume that the store does not possess "insider" knowledge about the evolution of these factors. Instead, the store randomly samples (with replacement) from the choice sets faced by consumer on past shopping trips. (Each such draw consists of the entire choice menu—including availabilities, prices, and wholesale costs—on a single shopping trip.) This allows for persistent variation across consumers in the composition of choice sets. (Such variation might be rooted in the size of the local

[56] While holding attrition constant.

store, the preferred time of day for shopping, etc.)

This procedure yields a synthetic dataset of future shopping trips. I then compute the choice probabilities associated with the future shopping trips within this synthetic dataset. Importantly, I accommodate endogenous learning *after* the stockout substitution. To see why this matters, consider a consumer who has never purchased a given brand b. Even if the store does not offer her one of b's products as a substitute, she still might learn her taste for the brand on a future trip if she elects to purchase one of its products. Endogenous learning may, therefore, reduce the potential returns to steering consumers' learning.

With choice probabilities in hand, I compute expected future profits. As I do so, I apply a 0.9998 real daily discount rate.[57]

Of course, this procedure reflects future profits under just one potential future state of the world. Accordingly, I repeat the entire procedure—synthesizing data and computing choice probabilities—several times in order to "integrate" over possible future states of the world. Finally, I average across these simulation rounds to obtain the present-discounted value of expected future profits associated with the acceptance or rejection of each available substitute. The "steering substitute" is then defined as the product that maximizes the sum of (i) the expected retail margins on the present shopping trip, and (ii) the present-discounted value of expected future profits.

Comparing the Profitability of the "Baseline" and "Steering" Policies.—Having characterized the "steering" substitution policy, I compare the expected profits under this hypothetical policy with those under the "baseline" policy. Here, I exploit the entirety of the data—including consumers' purchases after stockout substitutions.

Once more, the profits associated with a stockout substitute depend on the retail margin, the probability of acceptance, and the present-discounted value of expected profits (conditional on either acceptance or rejection). Regarding the probability of acceptance, I now leverage the entirety of the relevant consumer's observed choices—before, during, and after the stockout substitution—as I compute the conditional weights on the simulation draws of the random coefficients. As for future profits, I employ a similar heuristic to the one employed to characterize the "steering" substitution policy. Now, however, I impute the frequency of the consumer's future shopping trips as being the average across the entirety of her shopping trips in the data. Likewise, when simulating products' future availabilities, prices, and wholesale costs, I sample (with replacement) from the entirety of her shopping trips in the data.

Having computed the choice probabilities associated with future shopping trips, I calculate the expected future profits associated with the substitutes offered under the baseline and steering policies. This entire process is repeated several times (again, with a view to "integrating" over possible future

[57] This is roughly equivalent to a 0.93 real annual discount rate, which falls between the discount factor of 0.9 used by Ryan (2012) and the discount factor of 0.95 used by Collard-Wexler (2013).

states of the world). Finally, I compare the present-discounted value of expected profits under the baseline and "steering" policies by averaging across the simulations.

B. Counterfactual Results: Granola Bars

Table 6 compares outcomes under the "baseline" and "steering" substitution policies. (Recall that these are, respectively, the store's existing substitution policy and the one that maximizes the present-discounted value of expected profits.) Importantly, the scope to steer consumers' learning—and the profitability of doing so—depend on consumers' purchase histories. For instance, some consumers have previously purchased all three brands. As far as my demand model is concerned, the store cannot steer these consumers' learning, as they already know their tastes for all three brands. Other consumers, meanwhile, have exclusively purchased the highest-margin brand: Quaker. Although the store could introduce these consumers to one of the other brands (namely, Nature Valley and Sunbelt), doing so might, in fact, dent the store's future profits. When, therefore, does the store profit from steering consumers' learning? It emerges that the gains from steering consumers learning are concentrated in stockouts where (i) the out-of-stock product is sold under the budget brand, Sunbelt; and (ii) the consumer in question has *only* purchased the budget brand before. Here, the store can increase its future profits by a Quaker-branded substitute. (Quaker is preferable to Nature Valley because [i] the former brand affords slightly higher margins than the latter and [ii] the demand estimates suggest that consumers tend to learn more about Quaker than about Nature Valley.)[58] I will henceforth refer to stockouts of this description as "budget buyer" stockouts, and the remaining stockouts as "mainstream buyer" stockouts.

Panel A reports that the steering policy prescribes higher-margin substitutes than does the baseline policy. This disparity, which is pronounced for both the "budget buyer" and "mainstream buyer" stockouts ($1.30 and $1.03, respectively), is rooted in several factors. Concerning both the "budget buyer" and "mainstream buyer" stockouts, a smaller fraction of the steering substitutes are marked down than are their baseline counterparts.[59] The steering substitutes also tend to consist of larger packages than do their baseline counterparts (14.9 bars versus 8.3, respectively).[60] Finally, regarding

[58] In principle, the store could also benefit from introducing Quaker to consumers who have hitherto purchased only Sunbelt and Nature Valley. However, the gains from doing so are much more modest, as Quaker will cannibalize future sales from Nature Valley (which affords fairly high retail margins) as well as from Sunbelt (which affords thin margins.)

[59] Only 19.1% of the steering substitutes are marked down, versus 37.5% of the baseline substitutes.

[60] If the consumer is offered (and accepts) a large package of granola bars, she might wait longer before purchasing granola bars in the future. Hence, by offering a large package of granola bars as a stockout substitute, the store may be increasing present-trip profits at the expense of future-trip profits. Although my demand model abstracts from such dynamic considerations, they are likely of second-order importance. Survey evidence suggests that three quarters of American consumers purchase grocery groceries from two or more retailers each week (Acosta 2017). So, by offering a large package as a substitute, the store may in fact cannibalize its rivals' future sales (not its own). At all events, my abstraction from consumers' storage behavior should not distort estimates of the value of learning, as (i) the benefits of learning are realized on future shopping trips and (ii) I do not model consumers' learning in relation to quantity.

the "budget-buyer" stockouts in particular, the policies tend to recommend substitutes of different brands. Whereas the baseline policy typically selects a Sunbelt-branded substitute (thereby matching the brand of the out-of-stock product), the steering policy usually proposes a Quaker- or Nature Valley–branded substitute.[61]

Turning to the probability of acceptance, observe that the "baseline" policy delivers higher acceptance probabilities than the "steering" policy does. This is intuitive. Whereas the "baseline" policy tries to select the closest available substitute for the out-of-stock product, the "steering" policy sometimes picks a more distant substitute—either because it affords high retail margins, or because it introduces the consumer to a high-margin brand, or both. Notice also that the disparity in acceptance probabilities is larger for the "budget buyer" stockouts than for the "mainstream buyer" stockouts (22 percentage points versus 5 percentage points). Why is this the case? Regarding the "budget buyer" stockouts, recall that the steering policy seldom selects substitutes that match the brand of the out-of-stock product (namely, Sunbelt), whereas the baseline policy nearly always does. Concerning the "mainstream buyer" stockouts, by contrast, both policies tend to pick substitutes that share the same brand as the out-of-stock product.[62] As for the store's expected present-trip profits, these correspond to the average (across all stockouts) of the substitutes' respective retail margins and acceptance probabilities. It emerges that the "steering" policy delivers larger gains for the "mainstream buyer" stockouts than for the "budget buyer" stockouts.

Turning to future shopping trips, Panel B compares the two policies in relation to the present-discounted value of expected future profits, conditional on the consumer's accepting or rejecting the substitute. Mechanically, the two policies yield identical expected future profits if the consumer rejects the substitute, as she will not learn anything about it. If she accepts, by contrast, the store's choice of substitute may influence her learning and, by extension, her future purchases. Notice that the profitability of steering consumers' learning depends on their purchase histories. Regarding the "budget buyer" stockouts, the steering policy results in learning that increases the present-discounted value of expected future profits by \$0.22 on average (conditional on acceptance). This represents a 1.4% increase over the baseline present-discounted value of future profits of \$15.75 (again, conditional on acceptance). Concerning the "mainstream buyer" stockouts, by contrast, the steering policy delivers average future profits that are indistinguishable from those under the baseline policy. I will elaborate momentarily on why the gains from steering consumers' learning differ between the "steering" and "mainstream buyer" stockouts.

The present-discounted value of total profits corresponds to the sum of the expected present-trip margins and the present-discounted value of profits from future trips. Panel C indicates that the steering policy increases the present-discounted value of total profits by a nearly identical amount

[61] 93.8% and 4.1% of baseline and steering substitutes are Sunbelt-branded, respectively.

[62] 99.0% and 64.6% of baseline and steering substitutes, respectively, share the out-of-stock product's brand.

TABLE 6 – EXPECTED OUTCOMES UNDER "BASELINE" AND "STEERING" POLICIES
(PRODUCT CATEGORY: GRANOLA BARS)

	"Budget buyer" stockouts: only purchased Sunbelt so far[a]			"Mainstream buyer" stockouts: bought NV or Quaker before[b]		
	Baseline	Steering	Diff.	Baseline	Steering	Diff.
	Panel A. Present trip					
Retail margin	1.69	2.99	1.30	1.90	2.93	1.03
	(0.19)	(0.46)	(0.50)	(0.50)	(0.54)	(0.68)
Acceptance probability	0.95	0.73	–0.22	0.93	0.87	–0.05
	(0.10)	(0.24)	(0.21)	(0.12)	(0.17)	(0.15)
Expected present-trip profits	1.60	2.15	0.55	1.76	2.55	0.79
	(0.24)	(0.76)	(0.74)	(0.52)	(0.66)	(0.65)
	Panel B. Future trips					
PDV future profits, given accept	15.75	15.97	0.22	12.02	12.02	0.00
	(17.63)	(17.77)	(0.48)	(12.15)	(12.15)	(0.05)
PDV future profits, given reject	15.74	15.74	0.00	12.02	12.02	0.00
	(17.60)	(17.60)	(0.00)	(12.15)	(12.15)	(0.00)
	Panel C. Overall					
PDV total profits	17.34	18.04	0.70	13.78	14.57	0.79
	(17.63)	(17.76)	(0.88)	(12.20)	(12.23)	(0.65)

Notes: This table compares outcomes under two substitution policies: the store's existing policy (the "baseline"); and one that maximizes the PDV of expected profits (the "optimal" policy). All results are reported as means, with standard deviations appearing in parentheses.

[a] That is, both the out-of-stock product and the products that the consumer has previously purchased are sold under the Sunbelt brand. There are 97 such observations.

[b] That is, either the out-of-stock product is Nature Valley or Quaker, or at least one past purchase is Nature Valley or Quaker. There are 1951 such observations.

with respect to the "steering" and "mainstream buyer" stockouts: \$0.70 and \$0.79, respectively. However, this similarity masks an important difference between the two stockout types. Where the "mainstream buyer" stockouts are concerned, the gains under the steering policy are confined to the present shopping trip. Regarding the "budget buyer" stockouts, by contrast, \$0.15 of the gains (more than a fifth of the total) are realized on future shopping trips. These (expected) future gains reflect the budget buyers' learning about the mainstream brands.

Determinants of the Returns to Steering Consumers' Learning.—The counterfactual results point to meaningful variation in the profitability of steering consumers' learning. So far, I have analyzed this variation at a high level, focusing on the binary distinction between "budget buyer" stockouts, where the entirety of the consumer's orders/purchases are of the budget Sunbelt brand; and "mainstream buyer" stockouts, where either the out-of-stock product or a previous purchase are sold under a mainstream brand (i.e., Nature Valley or Quaker). Why is this distinction so important?

I will now explore the sources of this variation in the returns to steering consumers' learning. For simplicity, I focus on two key factors: (a) the brand of the out-of-stock product, and (b) the set of brands that she has bought before. Here, (a) is informative of the potential gains from steering the consumer's learning; all else equal, she is likelier to accept a substitute that is sold under the same brand as the out-of-stock product (or, failing that, a similar brand). And only if the consumer accepts will the store earn any retail margins, or the consumer learn her true tastes for the substitute's brand (if she does not know this already). As for (b), the set of brands that the consumer has previously purchased is informative of the possible gains from steering the consumer's learning because the consumer can only learn about brands that she has never purchased before.

How do these two factors—namely, the brand of the out-of-stock product and the set of brands the consumer has previously purchased—affect the returns to steering the consumer's learning? I adopt the following procedure to answer this question. First, I identify the "best" substitute from each brand, by which I mean the following. If the store were forced to offer a substitute of a given brand (such as Quaker), which of that brand's available products would maximize the present-discounted value of expected profits? Having identified the three brands' respective "best" substitutes for each stockout in the data, I then compare them in terms of retail margins, acceptance probabilities, and the store's present-discounted value of expected future profits (conditional on acceptance). This second step clarifies the trade-off between steering consumers' learning, on the one hand; and maximizing the probability of acceptance, on the other.

To see the intuition behind this exercise, consider the hypothetical stockout substitution depicted in Table 7. Here, the store needs to choose a stockout substitute for a consumer who had originally ordered Sunbelt Sweet & Salty granola bars. Six products remain available to serve as substitutes, two from each brand. For instance, within the Nature Valley brand, the store could either offer Sweet & Salty or Apple Crisp granola bars. My analysis would focus on the former because it affords a greater present-discounted value of expected profits (\$4 versus \$3). Put differently, conditional on the store's offering a Nature Valley–branded substitute, Sweet & Salty is the more promising choice. Likewise, for Quaker and Sunbelt, my analysis would focus on these brands' Chocolate Chip and Oatmeal Raisin granola bars, respectively. For expositional simplicity, these three products would be termed the "best" substitutes for their respective brands.

The results of this empirical exercise appear in Tables 8 and 9. The former table compares the retail margins and acceptance probabilities of the brands' respective "best" substitutes, while the latter table reports the present-discounted value of future profits conditional on acceptance. In both tables, results are decomposed based on (a) the brand of the out-of-stock product and (b) the brands that the consumer has previously purchased. (Results for combinations of [a] and [b] with fewer than 50 observations are relegated to Appendix E. I also omit the 73 observations in which one of the brands is completely out of stock.[63])

[63] More specifically, these are observations where the brand's top-selling products—i.e., those included in estimation—

Table 7 – Most Profitable Substitutes within Each Brand
(Hypothetical Stockout Substitution for Sunbelt Sweet & Salty)

	Nature Valley		Quaker		Sunbelt	
						
	Sweet & salty	Apple crisp	**Choc. chip**	Yogurt	Choc. chip	**Oatmeal raisin**
PDV profits ($)	**4**	3	**3**	2	2	**3**

Notes: This table depicts a hypothetical stockout substitution in which the out-of-stock product is Sunbelt Sweet & Salty. For each product on the shelf, the table reports the present-discounted value of expected profits conditional on the store's offering it as substitute. Within each brand, the product with the highest expected profits (emphasized) is the one that would be included in the empirical exercises presented in Tables 8 and 9. Images are taken from the brands' respective websites (and are property thereof).

Table 8 indicates that, on average, the retail margins of the "best" Quaker and Nature Valley substitutes exceed those of the "best" Sunbelt substitutes. As for acceptance probabilities, consumers are likelier to accept substitutes that share the same brand as the out-of-stock product. The latter result is consistent with the descriptive results presented in Section 3A.

Now consider the store's present-discounted value of *future* profits, conditional on acceptance. For a given stockout, the only source of variation between potential substitutes is learning. The results in Table 9 indicate that, under some circumstances, learning can perceptibly boost the store's (expected) future profits from a consumer. In particular, when a consumer has *only* purchased the low-margin "budget" brand, Sunbelt, the store's expected future profits increase by about thirty cents if the consumer accepts a Quaker or Nature Valley product as a substitute (thereby learning her true tastes for the high-margin brand in question). This means that, if a consumer has always opted for the (low-margin, budget-priced) Sunbelt brand, there is a nontrivial chance that if she tries either of the (high-margin, higher-priced) mainstream brands, she will be pleasantly surprised and purchase that mainstream brand again in the future.

Learning does not necessarily increase future profits, however. When a consumer has *only* purchased the mainstream brands on previous shopping trips (that is, Nature Valley and Quaker), her accepting a Sunbelt-branded product as a substitute would diminish the store's expected future profits by ten cents or so (depending on the brand of the out-of-stock product, as well as the set of mainstream brands that she has previously purchased). There is a risk that she likes Sunbelt more than she had expected and, consequently, purchases its (low-margin) products in the future.

are imputed as being entirely out of stock.

Table 8 – Retail Margins and Acceptance Probabilities of the "Best" Substitutes within Each Brand of Granola Bars

Brands bought before				Retail margins of brand's "best" substitute on shelf			Prob. accept brand's "best" substitute on shelf		
NV[a]	Quaker	Sunbelt	Obs.	NV[a]	Quaker	Sunbelt	NV[a]	Quaker	Sunbelt
Panel A. Out-of-stock product is Nature Valley (NV) brand									
Yes	No	No	187	2.16	3.00	1.77	0.91	0.62	0.53
				(0.50)	(0.51)	(0.17)	(0.12)	(0.25)	(0.28)
Yes	Yes	No	138	2.11	3.04	1.77	0.89	0.77	0.52
				(0.52)	(0.50)	(0.13)	(0.14)	(0.25)	(0.27)
Yes	Yes	Yes	51	2.08	2.97	1.94	0.89	0.70	0.57
				(0.48)	(0.53)	(1.11)	(0.09)	(0.23)	(0.32)
Panel B. Out-of-stock product is Quaker brand									
No	Yes	No	462	2.15	2.86	1.77	0.75	0.95	0.66
				(0.52)	(0.65)	(0.16)	(0.24)	(0.11)	(0.26)
No	Yes	Yes	109	2.20	2.78	1.76	0.65	0.91	0.68
				(0.46)	(0.68)	(0.15)	(0.26)	(0.12)	(0.32)
Yes	Yes	No	357	2.15	2.86	1.77	0.81	0.92	0.56
				(0.52)	(0.63)	(0.13)	(0.20)	(0.11)	(0.27)
Yes	Yes	Yes	146	2.20	2.95	1.76	0.77	0.85	0.67
				(0.49)	(0.61)	(0.14)	(0.21)	(0.17)	(0.32)
Panel C. Out-of-stock product is Sunbelt brand									
No	No	Yes	91	2.23	3.02	1.71	0.71	0.68	0.97
				(0.45)	(0.49)	(0.15)	(0.24)	(0.26)	(0.06)
No	Yes	Yes	70	2.23	2.97	1.72	0.66	0.79	0.97
				(0.50)	(0.54)	(0.13)	(0.24)	(0.26)	(0.05)
Yes	No	Yes	52	2.26	2.96	1.72	0.73	0.64	0.95
				(0.47)	(0.55)	(0.13)	(0.23)	(0.26)	(0.09)
Yes	Yes	Yes	99	2.21	2.95	1.70	0.76	0.79	0.96
				(0.50)	(0.53)	(0.14)	(0.24)	(0.21)	(0.07)

Notes: This table compares the retail margins of the "best" substitute within each brand, given the circumstances of the stockout substitution. By "best," I mean the following. Among each brand's available products, I identify the one that affords the highest present-discounted value of expected profits. Notice that results are decomposed based on the brand of the out-of-stock product (as indicated by the panels), as well as the set of brands that the consumer has previously purchased (as indicated by the leftmost trio of columns). For some combinations of (i) the brand of the out-of-stock product and (ii) the set of brands bought before, there is a negligible number of observations (specifically, 30 or fewer); these combinations are relegated to the Appendix. I also exclude observations where one (or more) of the brands was completely unavailable. (There are 73 such observations.) All reported numbers are means, with the standard deviations enclosed in parentheses.

[a] Nature Valley

Table 9 – PDV of Expected Future Profits by Brand of Substitute Granola Bars, Conditional on Acceptance

Brands bought before				PDV of expected future profits ($), given (accepted) substitute's brand		
Nature Valley	Quaker	Sunbelt	Obs.	Nature Valley	Quaker	Sunbelt
Panel A. Out-of-stock product is Nature Valley brand						
Yes	No	No	187	12.22	12.23	12.16
				(14.24)	(14.24)	(14.11)
Yes	Yes	No	138	10.04	10.04	9.95
				(9.72)	(9.72)	(9.74)
Yes	Yes	Yes	51	9.23	9.23	9.23
				(6.45)	(6.45)	(6.45)
Panel B. Out-of-stock product is Quaker brand						
No	Yes	No	462	14.25	14.26	14.17
				(12.68)	(12.68)	(12.62)
No	Yes	Yes	109	12.10	12.14	12.14
				(14.47)	(14.45)	(14.45)
Yes	Yes	No	357	11.90	11.90	11.82
				(11.34)	(11.34)	(11.35)
Yes	Yes	Yes	146	9.77	9.77	9.77
				(8.10)	(8.10)	(8.10)
Panel C. Out-of-stock product is Sunbelt brand						
No	No	Yes	91	15.55	15.62	15.32
				(16.19)	(16.34)	(16.10)
No	Yes	Yes	70	11.75	11.76	11.76
				(10.33)	(10.27)	(10.27)
Yes	No	Yes	52	11.75	11.74	11.75
				(11.07)	(11.18)	(11.07)
Yes	Yes	Yes	99	12.25	12.25	12.25
				(8.63)	(8.63)	(8.63)

Notes: This table compares the present-discounted value of profits of the "best" substitute within each brand. See Table 8 for details.

C. Counterfactual Results: Flavored Milk and Frozen French Fries

In this subsection, I briefly summarize the counterfactual results for the other two product categories that I study. Concerning consumers who suffer stockout substitutions for flavored milk and frozen french fries, the "steering" substitution policy increases profits by 2.5% and 2.4%, respectively. To what extent do these gains reflect learning, as opposed to increased present-trip profits? Recall that the demand estimates suggest that consumers learn less about these product categories than they do about granola bars. As a result, the gains from steering consumers' learning should be smaller for these categories than for granola bars. This intuition is supported by the counterfactual simulations, which are presented in Appendix Tables 11 and 14. Irrespective of the consumer's purchase history or the brand of the out-of-stock product, the store's choice of substitute has a modest effect on expected future profits. Regarding flavored milk, the store's present-discounted value of expected future profits increase by $0.01 under the steering policy with respect to stockouts where (i) the out-of-stock product is sold under the lowest-margin brand (namely, the private label); and (ii) the consumer has never purchased the highest-margin brand before (namely, TruMoo). As for frozen french fries, the store's choice of substitute has essentially no effect on expected future profits (regardless of the out-of-stock product's brand or the consumer's purchase history).

8. Conclusion

This paper shows that stockout substitutions in curbside grocery pickup enable the store to steer consumers' learning towards high-margin brands. However, consumers are less likely to accept substitutes from unfamiliar brands than they are to accept substitutes from familiar brands (whose products they've purchased before). To quantify the trade-off between steering consumers' learning and maximizing the probability of acceptance, I estimate a learning model of demand for differentiated products. Counterfactual simulations reveal that the returns to steering consumers' learning depend on their purchase histories, along with the extent of learning in the product category.

To my knowledge, this paper is the first to empirically characterize an optimal supply-side strategy to steer consumers' learning about experience goods. The task proves unusually tractable here for two reasons. First, consumers' learning about their tastes for groceries—along with their underlying preferences—can be represented by a comparatively simple demand model. And second, general equilibrium effects are negligible as far as stockout substitutions are concerned. That is, the focal store's optimal substitution policy does not depend on those of its competitors.

More broadly, my findings underline the need to understand the welfare effects of firms' efforts to steer consumers' learning. Firms do this in many ways: advertising (Anand and Shachar 2011; Ackerberg 2003), strategic pricing (Osborne 2011; Ching 2010), and the organization of products within a store (Poynor and Wood 2010), to name a few. The internet affords additional opportunities to steer consumers' learning. Concerning the opportunity studied in this paper—namely, stockout substitutions in curbside pickup—the welfare effects are negligible; someone's quality of life will not change if she tries a new brand of granola bars or chocolate milk due to a stockout substitution. However, in other online contexts, the welfare effects of steering consumers' learning may be substantial. Take the case of web browsers, which are used to access important productivity software—word processors, spreadsheets, calendars, etc.—and to casually surf the web (Taivalsaari et al. 2008). Here, Microsoft leverages the popularity of its Windows operating system to encourage consumers to try its own browser, Edge, and to discourage them from experimenting with those of its competitors (Krasnoff 2022; Hollister 2023).[64] Another example concerns online shopping, where Google exploits its dominance in web search to promote its eponymous shopping service (Raedts and Evans 2024).[65] Many of the affected consumers are, of course, happy with Edge or Google Shopping. Even so, some consumers might learn that they prefer alternatives—like Firefox or Bing Shopping, respectively—were they to try them. Future work could quantify the welfare effects of tech giants' efforts to steer consumers' learning about web browsers, online shopping, and other things.[66]

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[64] Microsoft sets Edge as the default browser on Windows 11 (Krasnoff 2022), so that web links and certain file types automatically open in Edge (unless consumers manually change the default browser). And when users try to download the rival Chrome browser, they are first presented with a notice that Edge ". . . runs on the same tech as Chrome, with the added trust of Microsoft," then asked to complete a poll about their reasons for downloading Chrome (Hollister 2023)

[65] When consumers make shopping-related searches, Google displays its own shopping service more prominently than those of its competitors (Raedts and Evans 2024).

[66] Unlike packaged foods, there are adjustment costs associated with trying out new online software/services. (For instance, when a consumer experiments with a new web browser, she needs to determine where important functions are located in the interface.) These adjustment costs affect welfare analysis as follows. If tech firms stopped steering consumers' learning, consumers might cross-shop online software/services more frequently. This would, in turn, increase the total adjustment costs incurred by consumers.

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Supplementary Appendix

A. Data Structure and Observable Characteristics

Illustrating the Structure of the Data.—Recall that Section 2A described a consumer who ordered Gala apples and Happy Egg eggs, only for the latter to go out of stock. Appendix Tables 1 and 2 portray what the curbside stockout data and scanner data would look like in this hypothetical case. Notice that the former lists the UPCs and product catalog descriptions of both the out-of-stock item and the substitute in my stylized example. However, the price of the out-of-stock product is missing (and must be imputed from other sales at the same store before and after the stockout).

As for the scanner data, Panels A and B of Appendix Table 2 compare the contents when the consumer accepts and rejects the substitute eggs, respectively.

State Dependence in Product, Brand, and Channel Choice.—Do consumers tend to purchase the same products in consecutive trips? Or at least products of the same brand? And how often do consumers switch shopping channels (i.e., in-store shopping versus curbside pickup versus home

Appendix Table 1 – Curbside Stockout Data (Example)

	Out-of-Stock Item	Offered Substitute
UPC	2430003110	1600027707
Description	"SUNBELT SWEET & SALTY PEANUT GRANOLA BAR 10.56 OZ"	"'NV SWT/SALTY BAR PEANUT 6CT/1.2OZ"
Substitute Only		
Price ($)		5.49
Accepted?		Yes

Note: The (counterfactual) purchase price of the out-of-stock item is not recorded in the data. I impute it using the scanner data.

Appendix Table 2 – Scanner Data (Example)

UPC	Product catalog description	Price ($)	Date	Store ID	Channel	Loyalty ID
Panel A. Substitute is accepted.						
81162002003	"FAIRLIFE MILK 2% CHOCOLATE 11.5 OZ"	4.79	01/01/2021	21	Pickup	12345
1600027707	"NV SWT/SALTY BAR PEANUT 6CT/1.2OZ"	3.79	01/01/2021	21	Pickup	12345
Panel B. Substitute is rejected.						
81162002003	"FAIRLIFE MILK 2% CHOCOLATE 11.5 OZ"	4.79	01/01/2021	21	Pickup	12345

Appendix Table 3 – State Dependence in Brand, Product, and Channel Choice

In consecutive trips, prob. of the same...	Flavored milk	Frozen french fries	Granola bars
	Panel A. Overall		
Product being purchased	0.603	0.364	0.382
Brand being purchased	0.769	0.691	0.686
Shopping channel	0.857	0.850	0.900
	Panel B. Conditional on present trip being curbside pickup		
Product being purchased	0.663	0.379	0.433
Brand being purchased	0.825	0.698	0.736
Shopping channel	0.738	0.746	0.775

Notes: Estimates are reported as means. Regarding curbside pickup: when there is a stockout substitution, I define the "purchased product" as being the stockout substitute, not the out-of-stock product (see Section 2C for a discussion).

delivery)?

To provide insight, Appendix Table 3 reports the probability of repeated product, brand, and shopping channel choices—both overall, and conditional on the present trip being curbside pickup. Focus first on the overall results, which are presented in Panel A. There are meaningful cross-category differences in the probability of purchasing the same product on consecutive trips. Whereas there is a 60.3% probability that a consumer purchases the same flavored milk on consecutive shopping trips, there is only a 36.4% (38.2%) that she does the same with respect to flavored french fries (granola bars). However, in all three categories, a consumer is likely to purchase products that are sold under the same brands on consecutive trips, with probabilities ranging from 68.6% (granola bars) to 76.9% (flavored milk). Furthermore, these purchases tend to be made through the same shopping channel. Across the three product categories, between 85% and 90% of consumers select the same shopping channel on consecutive trips.

Do consumers display more, or less, state dependence after a curbside pickup order? Panel B suggests that consumers' behavior evinces a similar degree of state dependence following curbside pickup versus in-store shopping or home delivery. The most perceptible difference concerns the choice of shopping channel. If a consumer has placed an order for curbside pickup, the probability that her next shopping trip shares the same channel (namely, curbside pickup) drops to 77.5% or less across the three product categories (compared to the unconditional probability of repeat channel choices of 85.0% across the three product categories).

B. Additional Descriptive Evidence

Reduced-Form Evidence on the Acceptance or Rejection of Substitutes.—In this subsection, I estimate a probit model in which the probability of acceptance depends on (i) the extent to which the substitute's characteristics resemble those of the out-of-stock product and (ii) whether the consumer has ever purchased products with the substitute's characteristics. Regarding (i), I construct a set of indicator variables for the substitute's sharing a given characteristic k (such as brand) with the out-of-stock product. Let $\text{same}_{ik} = 1$ if consumer i is offered a substitute that shares characteristic k with the out-of-stock product, and $\text{same}_{ik} = 0$ otherwise. As for (ii), I include a set of indicator variables for the substitute's sharing a given characteristic k with *any* of the products that the consumer has previously purchased. Formally, let $\text{ever}_{ik} = 1$ if consumer i is offered a substitute that shares characteristic k with any of the products that she has purchased on past shopping trips, and $\text{ever}_{ik} = 0$ otherwise.

Besides their observable characteristics, the prices of the out-of-stock product and substitute may also be informative of acceptance or rejection. In particular, the absolute value of the difference between the products' prices should be inversely associated with their substitutability. To see the intuition, consider the product category of sparkling water. Imagine that two consumers have experienced stockout, albeit for different products: whereas one has ordered thrifty private-label sparkling water, the other has ordered the premium Perrier brand. Now suppose that there are two potential substitutes on the shelf: Ice Mountain, a budget-oriented brand; and San Pellegrino, an upscale brand. Intuitively, the consumer who had originally ordered the private-label sparkling water would probably prefer the more inexpensive Ice Mountain sparkling water as a substitute, whereas the consumer who had originally ordered the Perrier would probably prefer the premium San Pellegrino. (Recall that consumers who accept stockout substitutions must pay the substitute's price, not that of the out-of-stock product.) To capture this effect within the probit model, I compute the absolute value of the difference between the substitute's price ($p_{i,\text{sub}}$) and that of the out-of-stock product ($p_{i,\text{OOS}}$).[67]

In all, I take the following probit model to the data. Letting $a_i = 1$ if consumer i accepts and $a_i = 0$ otherwise, I estimate:

$$a_i = \begin{cases} 1 & \text{if } a_i^\star \geqslant 0 \\ 0 & \text{if } a_i^\star < 0, \end{cases}$$

where

$$a_i^\star = \sum_{k=1}^{K} (\gamma_k \text{same}_{ik} + \zeta_k \text{ever}_{ik}) + \eta |p_{i,\text{sub}} - p_{i,\text{OOS}}| + \upsilon_i,$$

[67] As discussed in Section 2, I do not observe the out-of-stock product's price. Instead, I search the data for the nearest date on which the out-of-stock product was purchased at the store in question. Then I impute the out-of-stock product's price as being the average purchase price on the date in question. For details on how I impute prices, see Section 5.

and υ_i is distributed i.i.d. standard normal.

For each product category, Appendix Table 4 reports the average marginal effects of the relevant explanatory variables. As far as interpretation goes, it is instructive to compare the marginal effects of the two variables associated with a given observable characteristic k. These include: (a) whether the substitute shares characteristic k with the out-of-stock product (i.e., the same$_{ik}$ variables) and (b) whether the substitute shares characteristic k with any of the products purchased on past shopping trips (i.e., the ever$_{ik}$'s). The results suggest that (a) and (b) are of similar importance with respect to predicting acceptance. In particular, the average marginal effect associated with the same$_{ik}$ and ever$_{ik}$ variables are positive for eight of the thirteen characteristics studied. And of these positive marginal effects, six (five) are statistically significant for the same$_{ik}$'s (ever$_{ik}$'s).

That the average marginal effects of the same$_{ik}$ and ever$_{ik}$ variables are sometimes negative probably reflects the limitations of this reduced-form exercise. In particular, I have abstracted from the similarity or dissimilarity of specific brands or sizes. To more accurately capture the consumer's underlying choice problem, it helps to estimate a structural model (as I do in Sections 5 and 6).

Supplementary Evidence of Stockout Substitutions' Influence on Consumers' Learning.—The results in Table 4 suggest that stockout substitutions sometimes influence consumers' purchases through the mechanism of learning. This is because the future purchases of the "focal consumers" (who suffer stockout substitutions and, in consequence, can learn about the substitute's characteristics) differ from the future purchases of the "control consumers" (who order the same products as the focal consumers, but successfully pick up and thus do not learn about the substitute).

That the focal consumers proceed to purchase the substitute's brand more often in the future than do their "control" counterparts is consistent with the former's learning about the brand of the substitute. Specifically, some focal consumers may be discovering that they like the substitute's brand more than they had anticipated and, as a result, purchasing that brand on subsequent shopping trips. However, other factors could also explain the differences between focal and control consumers. One such factor is the "buy it again" feature of the online order system. When consumers visit the store's website or mobile app, consumers are presented with a list of items that they have purchased on previous shopping trips—any of which can be ordered again with a single click. (By contrast, ordering an item outside this list requires multiple steps; see Section 2A.) To test whether the "buy it again" list is responsible for the disparity between focal and control consumers, I repeat the descriptive exercise with one modification. Rather than comparing focal and control consumers with respect to all subsequent purchase—both online and offline—I instead focus solely on in-store purchases. If the disparity between focal and control consumers is entirely driven by the "buy it again" list (as opposed to learning), the disparity should disappear once analysis is confined to in-store purchases (where the "buy it again list" is irrelevant). Appendix Table 5 presents the results of this robustness check. Although the sample sizes shrink dramatically, the focal consumers still purchase the substitute's

Appendix Table 4 – Determinants of Acceptance: Average Marginal Effects from Probit Regressions

Variable	Flavored milk	Frozen french fries	Granola bars
	Product category		
Brand			
Sub shares OOS product's brand	0.019**	0.008*	0.082***
	(0.006)	(0.004)	(0.008)
Ever purchased sub's brand before	0.048***	0.028***	–0.016**
	(0.006)	(0.003)	(0.006)
Flavor			
Sub shares OOS product's flavor	0.153***	0.013**	0.070***
	(0.017)	(0.005)	(0.007)
Ever purchased sub's flavor before	0.027*	0.002	0.059***
	(0.012)	(0.005)	(0.006)
Size[a]			
Sub shares OOS product's size[a]	–0.042***	0.012***	
	(0.007)	(0.004)	
Ever purchased sub's size[a] before	–0.018**	0.007	
	(0.006)	(0.008)	
Pct. milkfat			
Sub shares OOS product's pct. milkfat	0.055***		
	(0.006)		
Ever purchased sub's pct. milkfat before	0.034***		
	(0.006)		
High protein status			
Sub shares OOS product's high protein status	0.072***		
	(0.021)		
Ever purchased sub's high protein status before	0.032		
	(0.021)		
Base vegetable			
Sub shares OOS product's base vegetable		0.117***	
		(0.014)	
Ever purchased sub's base vegetable before		–0.026**	
		(0.008)	
Texture			
Sub shares OOS product's texture			0.069***
			(0.013)
Ever purchased sub's texture before			0.005
			(0.010)
Calories			
Sub shares OOS product's calories			0.065***
			(0.006)
Ever purchased sub's calories before			0.001
			(0.007)

Appendix Table 4 (Continued)

Variable	Product category: Flavored milk	Frozen french fries	Granola bars
No. of bars			
Sub shares OOS product's no. of bars			–0.004
			(0.007)
Ever purchased sub's no. of bars before			–0.008
			(0.006)
|Sub's price – OOS product's price|	–0.053***	–0.017***	0.005
	(0.003)	(0.002)	(0.003)
Observations	15,191	29,238	18,432
Pseudo R^2	0.073	0.016	0.042

Notes: The dependent variable is whether a stockout substitute is accepted (=1) or rejected (=0). The table reports average marginal effects, not coefficients. Standard errors are in parentheses. (Because some households experience multiple stockouts, the standard errors are clustered at the household level.)

[a] Where sparkling water is concerned, the size of each individual can/bottle in the case.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

brand more frequently than do their control counterparts—at least where frozen french fries and granola bars are concerned.

There may also be underlying differences between the focal and control consumers. In particular, the focal consumers have, by construction, arrived at the store later than their control counterparts (as the stockout occurred in the interim). Could the pickup time be correlated with differential trends in future purchases? Such a correlation might arise if, for instance, the pickup time is associated with consumers' proclivity to experiment with unfamiliar products. To test for the presence of any such compositional differences between focal and control consumers, I repeat the descriptive exercise above with one modification: I now define the control consumer as the *first* consumer to successfully pick up the focal consumer's preferred product after it goes out of stock (from among the subset of consumers who, like the focal consumer, have never purchased the substitute's version of the relevant characteristic before).[68] Thus, the focal consumer's order must have been assembled *before* the control consumer's, so that either (a) the focal consumer placed her order earlier than did the control consumer or (b) the focal consumer's stated pickup time was earlier than the control consumer's. As a result, any compositional differences between focal and control consumers that are rooted in order or pickup times should be reversed. Reassuringly, the results—which are presented in Appendix Table 6—prove qualitatively similar to the ones above (albeit smaller in magnitude, perhaps due to the smaller sample

[68] In principle, this robustness check (unlike the main descriptive exercise above) is vulnerable to endogenous price changes. Specifically, the store might respond to a product's going out of stock by raising the price. This could cause the control consumer to face a different price from the focal consumer.

Appendix Table 5 – Successful Pickups versus Substitutions That (Might) Result in Learning: Robustness Check (In-Store Purchases Only)

Characteristic	Obs.	No. of purchases: Before stockout	No. of purchases: After stockout	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Suffer substitution	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Succesful pickup
			Panel A. Flavored milk		
Brand	49	31.4	14.0	0.039	0.096
		(41.5)	(19.8)	(0.135)	(0.260)
Pct. milkfat	12	18.6	8.0	0.208	0.159
		(34.7)	(7.9)	(0.305)	(0.293)
Size[a]	15	10.5	13.8	0.108	0.147
		(15.3)	(24.3)	(0.279)	(0.203)
			Panel B. Frozen french fries		
Brand	44	19.7	6.6	0.077	0.040
		(21.0)	(7.2)	(0.149)	(0.142)
Flavor	4	18.2	8.2	0.083	0.029
		(30.3)	(4.8)	(0.167)	(0.059)
Size[a]	12	28.9	6.5	0.000	0.000
		(59.4)	(7.8)	(0.000)	(0.000)
			Panel C. Granola bars		
Brand	21	24.8	5.0	0.146	0.089
		(29.8)	(4.8)	(0.301)	(0.241)
Calories[b]	4	20.9	10.8	0.028	0.048
		(15.6)	(9.2)	(0.056)	(0.060)
Flavor	45	45.3	12.7	0.056	0.037
		(54.5)	(20.8)	(0.185)	(0.102)
No. of bars	4	63.6	31.8	0.087	0.041
		(100.1)	(28.8)	(0.081)	(0.082)
Texture	8	38.6	14.9	0.013	0.194
		(41.3)	(14.8)	(0.035)	(0.274)

Notes: This table checks whether the results in Table 4 are robust to focusing solely on consumers' future *in-store* purchases. (This is because consumers' future in-store purchases will not be directly affected by the "buy-it-again" feature of the store's app and website.)

[a] Binned (small/medium/large)

[b] Binned (less than 100 cal; between 100 and 200 cal; more than 200 cal)

Appendix Table 6 – Successful Pickups After Stockouts versus Substitutions That (Might) Result in Learning: Robustness Check ("First After")

Characteristic	Obs.	No. of purchases: Before stockout	No. of purchases: After stockout	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Suffer substitution	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Succesful pickup
		Panel A. Flavored milk			
Brand	148	20.2	19.4	0.048	0.041
		(31.5)	(26.8)	(0.157)	(0.122)
Pct. milkfat	55	19.2	16.3	0.060	0.064
		(29.6)	(20.9)	(0.183)	(0.133)
Size[a]	36	8.9	16.5	0.171	0.139
		(12.0)	(20.3)	(0.288)	(0.250)
		Panel B. Frozen french fries			
Brand	98	12.8	7.8	0.086	0.042
		(20.9)	(12.2)	(0.217)	(0.119)
Flavor	17	17.5	10.3	0.140	0.112
		(39.8)	(20.9)	(0.227)	(0.182)
Size[a]	20	19.8	10.5	0.022	0.007
		(22.5)	(9.6)	(0.061)	(0.032)
		Panel C. Granola bars			
Brand	47	29.9	15.7	0.014	0.012
		(50.8)	(20.2)	(0.037)	(0.041)
Calories[b]	5	35.4	19.8	0.000	0.006
		(41.1)	(28.9)	(0.000)	(0.012)
Flavor	89	35.4	18.6	0.054	0.013
		(63.3)	(29.2)	(0.171)	(0.046)
No. of bars	9	10.9	15.1	0.148	0.042
		(13.4)	(18.5)	(0.213)	(0.057)
Texture	4	29.2	18.8	0.011	0.000
		(34.3)	(20.7)	(0.016)	(0.000)

Notes: This table examines whether the results in Table 4 are robust to considering a different population of "control consumers." Although the control consumer is drawn from the same pool of potential control consumers as in Table 4, here I select the first consumer to successfully pick up *after* the stockout event.

[a] Binned (small/medium/large)

[b] Binned (less than 100 cal; between 100 and 200 cal; more than 200 cal)

sizes).

C. Estimation Details

Simulated Likelihood Function.—I employ maximum simulated likelihood estimation to recover the parameters. The likelihood function is based on the probability of the consumer's ordering a particular good, as well as the probability of her accepting a specific substitute. Both those probabilities, in turn, depend on the goods' expected utilities at time t. However, the explanatory variables used in this learning model differ somewhat from those in a traditional mixed (or "random coefficients") logit model. Thus, I begin my derivation of the likelihood by showing how to compute the goods' expected utilities as a function of (a) the parameters indexing the distributions of consumer tastes and learning, as discussed above; and (b) consumers' observed choices in the data.

Equation equation (5) gives the consumer's expected utility of good j at time t, conditional on the set $\mathcal{I}_{it}$ of brands for which she fully knows her taste. All quantities in equation equation (5) are fully known to the consumer, with the possible exception of her time-t expected taste for good j's brand. This can be written as

$$\mathrm{E}[v_{iB(j)} \mid \mathcal{I}_{it}] = \underbrace{\mu_{iB(j)}}_{\substack{\text{prior expected}\\ \text{taste}}} + \underbrace{(v_{iB(j)} - \mu_{iB(j)})\, 1[B(j) \in \mathcal{I}_{it}]}_{\substack{\text{learning "correction" (if brand}\\ \text{was previously purchased)}}} \tag{8}$$

Here the indicator variable $1[B(j) \in \mathcal{I}_{it}]$ equals one if (and only if) the consumer knows her taste for brand $B(j)$ at time t. Until she purchases the brand for the first time, she does *not* fully know her taste for it and must, instead, rely on her prior expected taste $\mu_{iB(j)}$. But upon her first purchase of the brand, she learns the degree to which her true taste $v_{iB(j)}$ differs from her prior expected taste $\mu_{iB(j)}$.

In order to take equation equation (8) to the data, observe that prior expected tastes $\mu_{iB(j)}$ can be computed as the product of

(i) a $1 \times B$ vector of brand dummy variables, $\big(1[B(j) = 1], \ldots, 1[B(j) = B]\big)^\intercal$; and

(ii) a $B \times 1$ vector of prior expected brand tastes, $(\mu_{i1}, \ldots, \mu_{iB})$.

This is true because

$$\begin{aligned}
\mu_{iB(j)} &= \sum_{b=1}^{B} 1[B(j) = b] \cdot \mu_{ib} \\
&= \Big(1[B(j) = 1] \quad \cdots \quad 1[B(j) = B]\Big) \cdot \begin{pmatrix} \mu_{i1} \\ \vdots \\ \mu_{iB} \end{pmatrix}
\end{aligned} \tag{9}$$

The "learning correction" $(v_{iB(j)} - \mu_{iB(j)})$ can be calculated similarly. Here, the explanatory variables must account for the fact that the learning correction remains latent until the consumer buys the brand for the first time (formally, until $B(j) \in \mathcal{I}_{it}$). I therefore compute the learning correction as

(i) a $1 \times B$ vector of indicator variables, $\big(1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}], \ldots, 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}]\big)^\intercal$, such that entry b equals one if b is j's brand and also b is a brand the consumer has previously purchased (i.e., $b \in \mathcal{I}_{it}$); and

(ii) a $B \times 1$ vector of the consumer's "learning shocks," $(v_{i1} - \mu_{i1}, \ldots, v_{iB} - \mu_{iB})^\intercal$.

This representation is accurate because

$$\begin{aligned} v_{ib} - \mu_{ib} &= \sum_{b=1}^{B} 1[B(j) = b \text{ and } b \in \mathcal{I}_{it}](v_{ib} - \mu_{ib}) \\ &= \begin{pmatrix} 1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}] & \cdots & 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}] \end{pmatrix} \begin{pmatrix} v_{i1} - \mu_{i1} \\ \vdots \\ v_{iB} - \mu_{iB} \end{pmatrix} \end{aligned} \tag{10}$$

Importantly, the learning correction $(v_{ib} - \mu_{ib})$ has a mean of zero for all brands b. This follows from the fact that the consumer's prior expectation μ_{ib} on her taste for b is unbiased. (Recall that her true taste v_{ib} is drawn directly from her prior, which is normally distributed with mean μ_{ib}.) As a result, there is only one parameter to be estimated in connected with the learning correction: its standard deviation ι_b^2.

Unlike the random coefficients pertaining to brands, the remaining ones can be recovered with usual procedure employed in mixed (or "random-coefficients") logit, with x_j, p_{jt} and ξ_{jt} as explanatory variables.

The complete set of explanatory variables for good j can be represented by the vector

$$w_{jt} \equiv \begin{pmatrix} \Big(1[B(j) = b]\Big)_{b=1}^{B} \\ \Big(1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}], \cdots, 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}]\Big) \\ x_j \\ p_{jt} \\ 1[\text{before Jan. 2021 }] \cdot \tilde{\xi}_{jt} \\ 1[\text{after Jan. 2021 }] \cdot \tilde{\xi}_{jt} \\ 1[j = 0] \cdot 1[\text{reject in-person }] \end{pmatrix}$$

while the complete set of parameters can be written as

$$\chi_i \equiv \begin{pmatrix} (\mu_b)_{b=1}^{B} \\ (\nu_b - \mu_b)_{b=1}^{B} \\ \beta \\ \alpha \\ \lambda_{\text{pre-21}} \\ \lambda_{\text{post-21}} \\ \gamma \end{pmatrix}$$

Having written the expected utility of each good j as a function of the parameters to be estimated, as well as the data, I can now derive a parsimonious expression of the (simulated) likelihood function used in estimation. My estimation code borrows from Arteaga et al. (2022); while my exposition here borrows from the same, along with Train (2009). Before elaborating on the mechanics of estimation, I will introduce additional notation concerning an individual consumer's orders, substitutions, and learning. In reference to orders, let y_{ijt} equal one if consumer i orders good j in trip t, and zero otherwise. Likewise, in reference to substitutions, let a_{ijt} equal one if either (a) consumer i accepts good j as a substitute at time t, or (b) she is not offered j as a substitute at time t.[69] If neither (a) nor (b) hold—in other words, if the consumer has, in fact, been offered j' as a substitute and proceeded to reject it—then $a_{ij't}$ equals zero.

Take as given that consumer i has taste and learning parameters χ. Then, according to the familiar conditional logit formula, the probability that she orders good j at time t is

$$\begin{aligned} P_{ijt} \mid \chi &\equiv \Pr\left[j = \arg\max_{j \in \mathcal{J}_t} \mathrm{E}[u_{ijt}] \;\middle|\; w_t; \chi \right] \\ &= \frac{\exp(w_{jt}\chi)}{\sum_{j' \in \mathcal{J}_t} \exp(w_{j't}\chi)} \end{aligned}$$

while her probability of accepting the good as a substitute is given by

$$\begin{aligned} P^{A}_{ijt} \mid \chi &\equiv \Pr\left[\mathrm{E}[u_{ijt}] > u_{i0t} \;\middle|\; w_t; \chi \right] \\ &= \frac{\exp(w_{jt}\chi)}{1 + \exp(w_{jt}\chi)} \end{aligned}$$

However, due to the panel structure of the data, the consumer may make a sequence of multiple orders

[69] Either because she successfully picks up her original order (whether j or some other good), or because she is offered some other good j' as a substitute.

and substitution decisions. The probability of observing a given sequence takes the form

$$P_i \mid \chi \equiv \prod_{t \in \mathcal{T}} \prod_{j \in \mathcal{J}_t} (P_{ijt} \mid \chi)^{y_{ijt}} (P^A_{ijt} \mid \chi)^{a_{ijt}}$$

In reality, though, the consumer's individual taste coefficients are not observed by the econometrician. The unconditional choice-sequence probability P_i is obtained by integrating over the distribution of tastes across the population of consumers:

$$P_i \equiv \int (P_i \mid \chi) f_\chi(\chi) d\chi \tag{11}$$

Here $f_\chi(\cdot)$ denotes the probability density function (PDF) of the parameters χ. (Recall that these include the consumer's prior expected brand tastes [the μ_{ib}'s], her learning shocks [the $(v_{ib} - \mu_{ib})$'s], etc.)

As I previously mentioned, equation equation (11) does not possess a closed form, and must therefore be simulated. I do this with R random draws, indexed $r \in \{1, \ldots, R\}$. For each draw r, I draw a vector χ_r from $f_\chi(\chi)$ and then compute the choice probabilities conditional on χ_r, denoted $P_i \mid \chi_r$.

After conducting R draws and computing the resulting conditional choice probabilities, the simulated *unconditional* choice-sequence probability $\check{P}_i$ is computed as the average of the conditional choice probabilities:

$$\check{P}_i = \frac{1}{R} \sum_{r=1}^{R} \left(P_i \mid \chi^r \right) \tag{12}$$

For computational efficiency, this simulation is conducted simultaneously for all consumers i. The likelihood function is then computed as the product of the consumers' respective choice probabilities;

$$\check{\mathcal{L}} = \prod_{i \in \mathcal{N}} \check{P}_i$$

D. Estimation Results for Flavored Milk and Frozen French Fries

Appendix Tables 7 and 8 report the parameter estimates for the product categories of flavored milk and frozen french fries, respectively. Notice that the control function is omitted for the former product category. The reason is that the maximum simulated likelihood estimation fails to converge if the control function is included. This finding is not altogether unexpected. The purpose of the control function is to account for unobservable store- and time-specific promotional activities. And there is perhaps less scope for the store to engage in one form of promotion where flavored milk is concerned: namely, the physical organization of products within the category. For flavored milks need to be

Appendix Table 7 – Parameter Estimates for Demand Model
(Product Category: Flavored Milk)

	Panel A. Brands		
Variable	Mean expected tastes (μ_b's)	Heterogeneity of expected tastes (σ_b^2's)	Amount of learning (ι_b^2's)
Fairlife	4.187	4.660	0.476
	(0.092)	(0.037)	(0.018)
Private label	6.623	2.230	0.903
	(0.085)	(0.017)	(0.012)
TruMoo	6.219	1.951	1.648
	(0.085)	(0.020)	(0.019)
	Panel B. Non-brand observables and prices		
	Means (β's or α)	Standard deviations (σ_β^2's or σ_α^2)	
Low fat	0.619	3.458	
	(0.014)	(0.019)	
Size (oz.)	0.028		
	(0.000)		
Price[a]	0.690	1.438	
	(0.009)	(0.012)	
	Panel C. Other explanatory variables		
	Coefficient (γ)		
Reject in-person[b]	1.648		
	(0.138)		

Notes: estimates are based on 126,357 randomly-sampled observations, which involve 2048 households. 2810 of the observations are acceptances or rejections of stockout substitutes. Although standard errors are computed with the Halbert/White "robust" correction, they do not account for measurement error in the control function. (This measurement error should be neligible, however, as the control function is based on residuals of OLS regression with millions of store-product-time observations and only a handful of explanatory variables.)

[a] The distribution of price coefficients is assumed to be truncated normal, with support $(0, \infty)$.

[b] Until September 2021, consumers accepted or rejected stockout substitutes upon arrival at the store. Starting September 2021, they could accept or reject substitutes remotely (using the store's app or website).

refrigerated (and thus cannot be placed on endcaps).

E. Additional Counterfactual Simulations

Appendix Tables 9 and 10 compare various outcomes of interest—retail margins, acceptance probabilities, etc.—based on the brand of the substitute and on the consumer's past purchase history. Unlike

Appendix Table 8 – Parameter Estimates for Demand Model
(Product Category: Frozen French Fries)

Variable	Mean expected tastes (μ_b's)	Heterogeneity of expected tastes (σ_b^2's)	Amount of learning (ι_b^2's)
	Panel A. Brands		
Private label	4.516	2.666	0.145
	(0.099)	(0.030)	(0.016)
Ore-Ida	5.032	1.725	0.200
	(0.100)	(0.030)	(0.019)
	Panel B. Non-brand observables and prices		
	Means (β's or α)	Standard deviations (σ_β^2's or σ_α^2)	
Shape: regular-cut	–0.010	1.823	
	(0.016)	(0.018)	
Shape: shoestring	–0.887	2.409	
	(0.025)	(0.025)	
Shape: steak	–0.914	1.561	
	(0.022)	(0.020)	
Size (oz.)	0.045		
	(0.001)		
Zesty seasoning	–1.130	2.804	
	(0.039)	(0.036)	
Price[a]	–0.818	1.734	
	(0.083)	(0.056)	
	Panel C. Other explanatory variables		
	Coefficients (λ's or γ)		
Control function (pre-2021)[b]	0.474		
	(0.037)		
Control function (post-2021)[b]	–0.180		
	(0.028)		
Reject in-person[c]	0.617		
	(0.181)		

Notes: estimates are based on 54,253 randomly-sampled observations, which involve 2048 households. 2528 of the observations are acceptances or rejections of stockout substitutes. See notes beneath Appendix Table 7 for further discussion.

[a] The distribution of price coefficients is assumed to be truncated normal, with support $(0, \infty)$.

[b] The demand shocks are specified as $\xi_{jt} = \lambda \tilde{\xi}_{jt}$, where $\tilde{\xi}_{jt}$ is the residual from the pricing function and λ is a scaling parameter (reported here). See Section 5B for details.

[c] Until September 2021, consumers accepted or rejected stockout substitutes upon arrival at the store. Starting September 2021, they could accept or reject substitutes remotely (using the store's app or website).

Tables 8 and 9, which focus on past purchase histories with at least fifty observations, these tables instead attend to combinations with fewer than fifty.

Flavored Milk.—Appendix Table 11 compares expected outcomes under the "baseline" and "steering" substitution policies for the product category of milk. The left half of the table concerns stockout substitutions in which (i) the out-of-stock product is sold under the lowest-margin brand (namely, the private label); and (ii) the consumer has never purchased the highest-margin brand before (namely, TruMoo). These are the stockout substitutions with the largest returns to steering consumers' learning. As for the right half of the table, it collects the remaining stockout substitutions.

Appendix Table 9 – Retail Margins and Acceptance Probabilities of the "Best" Substitutes within Each Brand of Granola Bars: Purchase Histories with <50 Observations

Brands bought before				Retail margins of brand's "best" substitute on shelf			Prob. accept brand's "best" substitute on shelf		
NV[a]	Quaker	Sunbelt	Obs.	NV[a]	Quaker	Sunbelt	NV[a]	Quaker	Sunbelt
Panel A. Out-of-stock product is Nature Valley (NV) brand									
No	No	No	30	2.21	3.13	1.82	0.95	0.68	0.56
				(0.46)	(0.44)	(0.10)	(0.06)	(0.25)	(0.29)
No	No	Yes	7	2.30	2.91	1.80	0.94	0.75	0.76
				(0.46)	(0.53)	(0.09)	(0.04)	(0.16)	(0.30)
No	Yes	No	13	2.19	3.04	1.70	0.86	0.78	0.54
				(0.53)	(0.47)	(0.16)	(0.14)	(0.24)	(0.30)
No	Yes	Yes	5	2.43	3.27	1.80	0.91	0.87	0.59
				(0.21)	(0.05)	(0.07)	(0.10)	(0.13)	(0.31)
Yes	No	Yes	42	2.09	3.06	1.77	0.88	0.60	0.58
				(0.47)	(0.46)	(0.13)	(0.14)	(0.22)	(0.36)
Panel B. Out-of-stock product is Quaker brand									
No	No	No	43	2.08	2.94	1.76	0.64	0.88	0.49
				(0.53)	(0.59)	(0.14)	(0.31)	(0.14)	(0.32)
No	No	Yes	9	2.13	3.27	1.78	0.75	0.92	0.83
				(0.54)	(0.09)	(0.10)	(0.17)	(0.05)	(0.22)
Yes	No	No	36	2.16	2.92	1.78	0.78	0.86	0.49
				(0.47)	(0.66)	(0.13)	(0.19)	(0.17)	(0.25)
Yes	No	Yes	16	2.25	2.83	1.77	0.63	0.78	0.69
				(0.41)	(0.74)	(0.17)	(0.28)	(0.22)	(0.32)
Panel C. Out-of-stock product is Sunbelt brand									
No	No	No	4	2.32	3.25	1.73	0.76	0.84	0.82
				(0.25)	(0.07)	(0.16)	(0.15)	(0.13)	(0.17)
No	Yes	No	3	2.16	2.68	1.78	0.67	0.68	0.73
				(0.40)	(0.77)	(0.09)	(0.22)	(0.33)	(0.25)
Yes	No	No	4	1.54	2.77	1.74	0.74	0.53	0.59
				(0.14)	(0.62)	(0.07)	(0.18)	(0.27)	(0.33)
Yes	Yes	No	1	2.51	3.13	1.86	0.78	0.78	0.45
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: This table compares the retail margins of the "best" substitute within each brand, given the circumstances of the stockout substitution. The results are decomposed based on the brand of the out-of-stock product (as indicated by the panels), as well as the set of brands that the consumer has previously purchased (as indicated by the leftmost trio of columns). This table contains combinations with <50 observations; see Table 8 for combinations with $\geqslant$ 50 observations and further details about the simulation.

[a] Nature Valley

Appendix Table 10 – PDV of Expected Future Profits by Brand of Substitute Granola Bars, Conditional on Acceptance: Purchase Histories with <50 Observations

Brands bought before				PDV of expected future profits ($), given (accepted) substitute's brand		
Nature Valley	Quaker	Sunbelt	Obs.	Nature Valley	Quaker	Sunbelt
Panel A. Out-of-stock product is Nature Valley brand						
No	No	No	30	16.35	16.36	15.72
				(15.63)	(15.62)	(15.27)
No	No	Yes	7	9.95	9.75	9.78
				(13.38)	(13.44)	(13.37)
No	Yes	No	13	7.87	7.88	7.84
				(9.48)	(9.47)	(9.48)
No	Yes	Yes	5	7.14	7.22	7.22
				(10.25)	(10.30)	(10.30)
Yes	No	Yes	42	8.58	8.51	8.58
				(7.45)	(7.55)	(7.45)
Panel B. Out-of-stock product is Quaker brand						
No	No	No	43	14.66	14.69	14.33
				(19.43)	(19.45)	(19.17)
No	No	Yes	9	7.32	7.25	7.17
				(6.06)	(6.11)	(6.12)
Yes	No	No	36	6.75	6.75	6.76
				(7.24)	(7.24)	(7.18)
Yes	No	Yes	16	8.46	8.34	8.46
				(8.60)	(8.66)	(8.60)
Panel C. Out-of-stock product is Sunbelt brand						
No	No	No	4	9.28	9.29	8.92
				(7.63)	(7.62)	(7.39)
No	Yes	No	3	13.21	13.22	13.11
				(10.05)	(10.07)	(10.13)
Yes	No	No	4	2.75	2.75	2.78
				(0.93)	(0.93)	(0.89)
Yes	Yes	No	1	10.05	10.05	10.05
				(0.00)	(0.00)	(0.00)

Notes: This table compares the present-discounted value of profits of the "best" substitute within each brand. See Appendix Table 9 for details.

Appendix Table 11 – Expected Outcomes under "Baseline" and "Steering" Policies (Product Category: Flavored Milk)

	"Non-TruMoo buyer" stockouts: never purchased TruMoo before[a]			"Mainstream buyer" stockouts: bought TruMoo before[b]		
	Baseline	Optimal	Diff.	Baseline	Optimal	Diff.
	Panel A. Present trip					
Retail margin	2.12	3.15	1.03	2.26	3.26	0.99
	(0.70)	(0.49)	(0.71)	(0.70)	(0.53)	(0.80)
Acceptance probability	0.91	0.90	−0.01	0.94	0.92	−0.02
	(0.16)	(0.16)	(0.19)	(0.13)	(0.14)	(0.15)
Expected present-trip profits	1.94	2.82	0.88	2.15	2.99	0.85
	(0.76)	(0.65)	(0.74)	(0.76)	(0.66)	(0.81)
	Panel B. Future trips					
PDV future profits, given accept	30.50	30.50	0.01	31.67	31.67	0.00
	(25.33)	(25.33)	(0.08)	(25.29)	(25.29)	(0.04)
PDV future profits, given reject	30.50	30.50	0.00	31.67	31.67	0.00
	(25.33)	(25.33)	(0.00)	(25.29)	(25.29)	(0.00)
	Panel C. Overall					
PDV total profits	32.44	33.32	0.88	33.81	34.66	0.85
	(25.42)	(25.38)	(0.74)	(25.36)	(25.36)	(0.80)

Notes: This table compares outcomes under two substitution policies: the store's existing policy (the "baseline"); and one that maximizes the PDV of expected profits. All results are reported as means, with standard deviations appearing in parentheses.

[a] That is, neither the out-of-stock product, nor the products that the consumer has previously purchased are sold under the TruMoo brand. There are 246 such observations.

[b] That is, either the out-of-stock product is TruMoo, or at least one past purchase is TruMoo. There are 1802 such observations.

Appendix Table 12 – Retail Margins and Acceptance Probabilities of the "Most Profitable" Substitutes within Each Brand of Flavored Milk

Brands bought before				Retail margins of brand's most profitable substitute on shelf			Prob. accept brand's most profitable substitute on shelf		
Fairlife	Pvt. lbl.	TruMoo	Obs.	Fairlife	Pvt. lbl.	TruMoo	Fairlife	Pvt. lbl.	TruMoo
Panel A. Out-of-stock product is Fairlife brand									
No	Yes	Yes	5	2.44	2.73	2.74	0.96	0.99	0.99
				(0.69)	(0.38)	(0.84)	(0.04)	(0.02)	(0.01)
Yes	No	No	50	2.85	3.03	3.46	1.00	0.90	0.89
				(0.44)	(0.24)	(0.63)	(0.01)	(0.10)	(0.11)
Yes	No	Yes	18	2.77	2.84	3.43	0.99	0.88	0.88
				(0.42)	(0.47)	(0.55)	(0.02)	(0.18)	(0.20)
Yes	Yes	No	23	2.80	3.04	3.20	1.00	0.97	0.93
				(0.53)	(0.17)	(0.77)	(0.00)	(0.05)	(0.07)
Yes	Yes	Yes	51	2.85	3.03	3.35	0.98	0.96	0.93
				(0.49)	(0.19)	(0.70)	(0.08)	(0.07)	(0.14)
Panel B. Out-of-stock product is private label									
No	No	Yes	6	2.97	1.84	3.62	0.60	0.98	0.98
				(0.32)	(0.59)	(0.44)	(0.26)	(0.02)	(0.02)
No	Yes	No	123	2.72	2.56	3.08	0.47	0.96	0.75
				(0.55)	(0.64)	(0.76)	(0.30)	(0.10)	(0.32)
No	Yes	Yes	541	2.72	2.45	3.13	0.43	0.95	0.86
				(0.60)	(0.63)	(0.77)	(0.28)	(0.11)	(0.23)
Yes	No	No	3	3.16	3.07	2.56	0.77	0.88	0.73
				(0.43)	(0.06)	(0.86)	(0.19)	(0.00)	(0.27)
Yes	No	Yes	3	2.61	2.09	2.81	0.93	0.92	0.92
				(0.54)	(0.64)	(0.70)	(0.06)	(0.09)	(0.09)
Yes	Yes	No	28	2.97	2.57	3.09	0.75	0.96	0.79
				(0.35)	(0.60)	(0.77)	(0.28)	(0.10)	(0.24)
Yes	Yes	Yes	184	2.82	2.43	3.19	0.73	0.97	0.87
				(0.55)	(0.64)	(0.74)	(0.29)	(0.08)	(0.21)
Panel C. Out-of-stock product is TruMoo									
No	No	No	1	3.40	2.88	3.78	0.47	0.71	0.80
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No	No	Yes	49	2.89	2.87	3.08	0.51	0.80	0.89
				(0.48)	(0.51)	(0.79)	(0.27)	(0.24)	(0.18)
No	Yes	No	7	2.81	2.66	2.85	0.54	0.89	0.80
				(0.52)	(0.61)	(0.81)	(0.25)	(0.18)	(0.31)
No	Yes	Yes	327	2.83	2.92	2.90	0.46	0.92	0.88
				(0.54)	(0.42)	(0.84)	(0.25)	(0.15)	(0.21)
Yes	No	No	1	2.76	2.84	2.27	1.00	0.98	0.99
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Yes	No	Yes	28	3.08	2.75	3.22	0.82	0.86	0.92
				(0.39)	(0.46)	(0.72)	(0.29)	(0.20)	(0.17)
Yes	Yes	No	5	3.22	2.50	2.60	0.85	1.00	0.99
				(0.41)	(0.56)	(0.67)	(0.16)	(0.00)	(0.01)
Yes	Yes	Yes	150	2.84	2.93	2.82	0.77	0.95	0.91
				(0.50)	(0.39)	(0.81)	(0.29)	(0.11)	(0.17)

Notes: This table compares the present-discounted value of profits of the "most profitable" substitute within each brand. See notes to Table 8 for details. (203 observations are excluded because one or more brands' products are entirely out-of-stock.)

Appendix Table 13 – PDV of Expected Future Profits, Conditional on Acceptance
Product Category: Flavored Milk

Brands bought before				PDV of expected future profits ($), given (accepted) substitute's brand		
Fairlife	Pvt. lbl.	TruMoo	Obs.	Fairlife	Pvt. lbl.	TruMoo
Panel A. Out-of-stock product is Fairlife brand						
No	Yes	Yes	5	15.60	15.55	15.55
				(7.58)	(7.54)	(7.54)
Yes	No	No	50	34.46	34.44	34.40
				(18.79)	(18.79)	(18.79)
Yes	No	Yes	18	30.39	30.43	30.39
				(18.52)	(18.56)	(18.52)
Yes	Yes	No	23	36.17	36.17	36.17
				(22.08)	(22.08)	(22.08)
Yes	Yes	Yes	51	37.70	37.70	37.70
				(23.75)	(23.75)	(23.75)
Panel B. Out-of-stock product is private label						
No	No	Yes	6	8.48	8.45	8.49
				(6.92)	(6.90)	(6.93)
No	Yes	No	123	35.09	35.09	35.06
				(25.54)	(25.54)	(25.54)
No	Yes	Yes	541	34.74	34.72	34.72
				(27.09)	(27.07)	(27.07)
Yes	No	No	3	7.75	7.74	7.74
				(5.36)	(5.35)	(5.35)
Yes	No	Yes	3	7.05	7.05	7.05
				(6.96)	(6.96)	(6.96)
Yes	Yes	No	28	29.45	29.45	29.46
				(23.41)	(23.41)	(23.41)
Yes	Yes	Yes	184	31.01	31.01	31.01
				(24.39)	(24.39)	(24.39)
Panel C. Out-of-stock product is TruMoo brand						
No	No	No	1	2.49	2.49	2.50
				(0.00)	(0.00)	(0.00)
No	No	Yes	49	33.58	33.56	33.59
				(27.20)	(27.21)	(27.21)
No	Yes	No	7	35.19	35.19	35.17
				(32.32)	(32.33)	(32.34)
No	Yes	Yes	327	31.74	31.73	31.73
				(25.82)	(25.81)	(25.81)
Yes	No	No	1	9.37	9.37	9.36
				(0.00)	(0.00)	(0.00)
Yes	No	Yes	28	29.36	29.37	29.36
				(25.16)	(25.16)	(25.16)
Yes	Yes	No	5	12.38	12.38	12.40
				(7.09)	(7.09)	(7.10)
Yes	Yes	Yes	150	34.57	34.57	34.57
				(27.21)	(27.21)	(27.21)

Notes: This table compares the present-discounted value of profits of the "most profitable" substitute within each brand. See Appendix Table 12 for details.

Appendix Table 14 – Expected Outcomes under "Baseline" and "Steering" Policies (Product Category: Frozen French Fries)

	"Budget buyer" stockouts: never purchased Ore-Ida before[a]			"Mainstream buyer" stockouts: bought Ore-Ida before[b]		
	Baseline	Optimal	Diff.	Baseline	Optimal	Diff.
	Panel A. Present trip					
Retail margin	1.92	2.02	0.10	1.71	2.01	0.30
	(0.28)	(0.18)	(0.21)	(0.33)	(0.20)	(0.32)
Acceptance probability	0.95	0.98	0.04	0.94	0.95	0.00
	(0.10)	(0.04)	(0.09)	(0.11)	(0.09)	(0.11)
Expected present-trip profits	1.83	1.99	0.16	1.61	1.91	0.30
	(0.35)	(0.20)	(0.28)	(0.36)	(0.26)	(0.32)
	Panel B. Future trips					
PDV future profits, given accept	9.21	9.21	0.00	9.54	9.54	0.00
	(8.47)	(8.47)	(0.00)	(7.25)	(7.25)	(0.00)
PDV future profits, given reject	9.21	9.21	0.00	9.54	9.54	0.00
	(8.47)	(8.47)	(0.00)	(7.25)	(7.25)	(0.00)
	Panel C. Overall					
PDV total profits	11.03	11.20	0.16	11.16	11.45	0.30
	(8.45)	(8.46)	(0.28)	(7.24)	(7.24)	(0.31)

Notes: This table compares outcomes under two substitution policies: the store's existing policy (the "baseline"); and one that maximizes the PDV of expected profits (the "optimal" policy). All results are reported as means, with standard deviations appearing in parentheses.

[a] That is, neither the out-of-stock product, nor the products that the consumer has previously purchased are sold under the Ore-Ida brand. There are 500 such observations.

[b] That is, either the out-of-stock product is Ore-Ida, or at least one past purchase is Ore-Ida. There are 1548 such observations.

Appendix Table 15 – Retail Margins and Acceptance Probabilities of the "Most Profitable" Substitutes within Each Brand of Frozen French Fries

Brands bought before			Retail margins of brand's most profitable substitute on shelf		Prob. accept brand's most profitable substitute on shelf	
Pvt. lbl.	Ore-Ida	Obs.	Pvt. lbl.	Ore-Ida	Pvt. lbl.	Ore-Ida
Panel A. Out-of-stock product is private label						
No	No	5	1.50	1.80	0.88	0.77
			(0.13)	(0.54)	(0.15)	(0.19)
No	Yes	56	1.55	2.03	0.92	0.95
			(0.10)	(0.25)	(0.10)	(0.09)
Yes	No	151	1.55	1.98	0.97	0.85
			(0.09)	(0.28)	(0.07)	(0.19)
Yes	Yes	692	1.54	2.02	0.97	0.92
			(0.10)	(0.23)	(0.07)	(0.15)
Panel B. Out-of-stock product is Ore-Ida						
No	No	8	1.53	2.07	0.83	0.98
			(0.10)	(0.08)	(0.16)	(0.03)
No	Yes	474	1.53	2.01	0.87	0.99
			(0.09)	(0.21)	(0.12)	(0.04)
Yes	No	14	1.57	2.09	0.96	0.96
			(0.10)	(0.14)	(0.05)	(0.04)
Yes	Yes	538	1.54	2.02	0.93	0.97
			(0.09)	(0.22)	(0.10)	(0.08)

Notes: This table compares the present-discounted value of profits of the "most profitable" substitute within each brand. See notes to Table 8 for details. (110 observations are excluded because one or more brands' products are entirely out-of-stock.)

Appendix Table 16 – PDV of Expected Future Profits, Conditional on Acceptance
Product Category: French Fries

Brands bought before			PDV of expected future profits ($), given (accepted) substitute's brand	
Pvt. lbl.	Ore-Ida	Obs.	Pvt. lbl.	Ore-Ida
Panel A. Out-of-stock product is private label				
No	No	5	6.85	6.85
			(2.23)	(2.23)
No	Yes	56	7.70	7.70
			(5.75)	(5.75)
Yes	No	151	10.76	10.76
			(8.92)	(8.92)
Yes	Yes	692	10.00	10.00
			(7.61)	(7.61)
Panel B. Out-of-stock product is Ore-Ida				
No	No	8	16.64	16.64
			(23.54)	(23.54)
No	Yes	474	9.08	9.08
			(7.99)	(8.00)
Yes	No	14	9.81	9.81
			(10.42)	(10.42)
Yes	Yes	538	9.01	9.01
			(6.42)	(6.42)

Notes: This table compares the present-discounted value of profits of the "most profitable" substitute within each brand. See notes to Appendix Table 15 and Table 8 for details.