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

Andrew Zeyveld*

October 8, 2024

Click here for the latest version

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. The store can, therefore, increase its future profits by selecting stockout substitutes that belong to profitable brands the consumers have never tried before. Some consumers will learn that they like the substitute's brand and then purchase its (profitable) products on subsequent shopping trips. However, I find that consumers are less likely to accept such substitutes than they are to accept substitutes whose brands are more familiar. To quantify the trade-off between steering consumers' learning and maximizing the probability of substitutes' being accepted, I estimate a learning-based model of differentiated products demand. Counterfactual simulations suggest that the profitability of steering consumers' learning depends on the amount of learning within the relevant product category, as well as on individual consumers' purchase histories.

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

*Department of Economics, Michigan State University. E-mail: zeyveld@msu.edu
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 and the MSU EML 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

In curbside pickup, consumers order groceries online and then pick them up from their local supermarket. However, sometimes 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.[1]

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 more likely to purchase profitable products in the future. To see the intuition, consider a consumer who typically orders unprofitable products. On one occasion, however, her preferred (unprofitable) product goes out of stock. In its place, she is offered a profitable 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, such an attempt to steer her learning is not without risk. She may be less likely to accept an unfamiliar product as a substitute than a product that she has previously purchased. And if she is unhappy with the store's handling of the substitution, she may patronize the store less frequently in the future (or even stop visiting altogether).

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 show that stockout substitutions influence consumers' learning about their tastes for *brands* (by which I mean branded product lines, like the "Nature Valley" brand of granola bars). However, I also find that consumers tend to prefer substitutes that do *not* result in learning. Instead, they favor substitutes that belong to brands they have previously purchased. This creates a strategic trade-off for the store. On the one hand, it can exploit stockout substitutions to steer consumers' learning towards profitable brands, thereby increasing its future profits. On the other hand, consumers are likelier to reject stockout substitutes that belong to unfamiliar brands (and might even curtail their future patronage of the store as a result). To quantify this trade-off, I estimate a learning model of demand for differentiated products. Then I use the model to conduct counterfactual simulations, with a view to characterizing the optimal substitution policy.

The demand estimates suggest that consumers learn more in relation to some product categories than others. This heterogeneity proves important with respect to the optimal substitution policy. Regarding one of the three product categories studied—namely, granola bars—the store can substantially increase its expected future profits by steering consumers' learning. But where the other two product categories

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

are concerned—namely, flavored milk and frozen french fries—steering consumers' learning yields small returns.

In Section 2, I provide institutional background and then introduce the data. This study concerns a supermarket chain that offers three ways to shop: in-person shopping, home delivery, and curbside pickup. It is in the last of these shopping channels that "stockout substitutions" occur. For each substitution, I observe the out-of-stock item and the substitute, as well as the consumer's decision to accept or reject the latter. Stockout substitutions aside, I also observe so-called "scanner data" that record consumers' purchases at the store. Importantly, the scanner data are at the household-panel level. This enables me to compare an individual consumer's purchases before versus after a stockout substitution.

In Section 3, I present descriptive evidence of the trade-offs faced by the store as it chooses stockout substitutes. First, I consider why consumers accept or reject stockout substitutes. I find that the probability of acceptance is increasing in the similarity of the substitute's observable characteristics—such as brand or such—to those of (i) the out-of-stock product and (ii) products that the consumer has previously purchased. Next, 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 whose brand they have never purchased before, they are more likely to purchase that brand's products in the future (relative to the counterfactual where no stockout occurred). By contrast, I do not find comparable evidence that consumers learn about their tastes other characteristics, such as size. This is intuitive; consumers are unlikely to learn much from, say, purchasing a 16-pack of granola bars for the first time. Finally, I study the determinants of products' profitability, as measured by their retail margins (i.e., retail price minus wholesale cost). I find that a product's brand is among the primary determinants of its margins.

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 may find that they like the high-margin brands and, in consequence, purchase the brands' products in the future. On the other hand, consumers tend to prefer substitutes that resemble either the out-of-stock product or products that they have previously purchased. So, if the store offers a substitute whose brand is unfamiliar to the consumer, she may be disposed to reject it. (And if she is acutely annoyed with the store's handling of the substitution, she may reduce her future patronage of the store.)

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 outcomes under counterfactual substitution policies. What is the optimal substitution policy, given that stockout substitutions influence consumers' learning? In answering this question, I face an empirical challenge: the data do not identify the relationship between stockout substitutions and consumer attrition. That is, I cannot determine whether the store's offering a counterfactual substitute would have caused the consumer to curtail her future patronage of the store. Section 7 presents my response to this empirical challenge. Initially, I assume that the store's choice of substitute does not affect consumer attrition. This enables me to identify a *conditionally* optimal substitution policy. Then I compare the expected profits under this counterfactual policy (which consciously steers consumers' learning) with the expected profits under the store's existing substitution policy (which does *not* steer consumers' learning). This yields an upper bound on the profitability of steering consumers' learning. Next, I identify the stockouts with the highest resturns to steering consumers' learning. Concerning these stockouts, I ask whether the gains from steering consumers' learning are likely to exceed any (potential) increases in consumer attrition. The answer to this question appears to vary across product categories. Concerning flavored milk and frozen french fries—where the demand estimates point to little consumer learning—there are small returns to steering consumers' learning. It is, therefore, plausible that the gains from steering consumers' learning might be outweighed by (possible) increases in consumer attrition. But regarding granola bars, where the demand estimates point to meaningful learning, there is scope to materially increase future profits by steering consumers' learning. These gains prove to be concentrated in stockouts where the consumer has *only* purchased a (low-margin) budget brand in the past. The store can substantively increase its expected future profits from such a consumer by offering her a substitute from a (high-margin) mainstream brand. The returns to steering such consumers' learning are likely to exceed any increases in attrition that may result.

Related Literature.—Consumers often possess incomplete information. This has motivated an extensive literature on the effects of informational interventions. In contexts ranging from health insurance enrollment (Kling et al. 2012) to school choice (Hastings and Weinstein 2008), and from electricity consumption (Jessoe and Rapson 2014) to the avoidance of air pollution (Barwick et al. 2024), there is evidence that learning changes consumers' choices.

Most prior work on consumer learning belongs to the field of public economics. Here, the question is whether the government can improve consumers' welfare by providing them with more information. To get at this question, studies in this literature typically employ randomized control trials (RCTs).[2] Part of the attraction of RCTs is the difficulty of identifying consumers' learning in observational data (see Shin, Misra, and Horsky [2012] and Ching [2010 a,b]).

This paper, by contrast, joins the smaller literature on consumer learning within the field of empirical

[2] Representative exceptions include Barwick et al. (2024); Bollinger, Leslie, and Sorensen (2011); and Mastromonaco (2015).

industrial organization (IO). Importantly, 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.

A firm can employ many methods to steer consumers' learning. For instance, advertising helps inform consumers about the firm's offerings (Ackerberg 2003; Anand and Shachar 2011). The firm might also lower its prices, both to *encourage* consumers to try its own products (Osborne 2011), and to *discourage* consumers from trying those of its competitors (Ching 2010). The growth of online shopping presents further opportunities to steer consumers' learning, including (but certainly not limited to) the stockout substitutions studied in this paper.[3]

The literature on consumer learning within empirical IO faces significant empirical challenges. On the demand side, it is difficult to identify consumers' learning from aggregated data on market shares (Ching 2010). Although household-level panel data facilitate identification, they also increase the computational burden. This limits the sort of learning model that can be estimated. To the best of the author's knowledge, no empirical work combines all the following features: (i) forward-looking consumers, (ii) heterogeneous underlying preferences, and (iii) a gradual (i.e., Bayesian) learning process.[4] Turning to the supply side, it is difficult to characterize firms' optimal strategies in general equilibrium. For, when one firm tries to steer consumers' learning (say, by lowering prices or by advertising), its rivals may respond in kind.

I study a setting where these empirical challenges are unusually tractable: curbside grocery pickup. On the demand side, a simple learning model provides a realistic approximation of consumers' behavior. Because packaged foods are highly standardized and have just one usage case (namely, snacking), I can adopt a "one-shot" model of learning, where a single consumption experience suffices for a consumer to learn her tastes for given brand.[5] Additionally, grocery shopping is characterized by many fast-paced, low-stakes decisions, so it seems plausible that consumers focus on their present-trip utility (as opposed to solving the complex dynamic problem induced by the future expected value of learning). Consequently, I can approximate consumers' behavior as being myopic, as opposed to forward-looking. As for the supply side, general equilibrium effects are negligible where the store's stockout substitution policy is concerned; one store's substitution policy is unlikely to influence another's.[6] I can, therefore, characterize the optimal supply-side strategy to

[3]In Section 8, I describe other online

[4]By "forward looking," I mean that consumers are cognizant of the expected future value of learning their tastes for additional products. By "heterogeneous underlying preferences," I mean that some consumers derive greater utility from a given good than others do. And by a "gradual learning process," I mean that consumers progressively learn more about their tastes for a given product through repeated consumption experiences.

[5]This contrasts with a more complex Bayesian learning model, in which consumers gradually learn their tastes for brands through repeated purchase experiences.

[6]These policies are generally chain-wide. And any change in the substitution policy would presumably incur substantial costs with retraining workers, altering computer algorithms, etc.

steer consumers' learning.[7] This task has proved intractable in prior work, which concerns settings where general equilibrium factors play a more important role.

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 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

[7] Albeit, conditional on consumers' future choices of shopping outlet being unaffected by (reasonable) changes in the store's substitution policy. See Section 7 for details.

[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.

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 (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,

---

[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 consumers rarely 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.

[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.

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 (provided that she participates in the chain's loyalty program). 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.[16] 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.[17] 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 (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

[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]The store maintains the same prices in-store as online.

[17]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.

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.[18] (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.[19] 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 within the category. For structural estimation to be feasible, consumers' preferences should mostly depend on a few product characteristics: brand, size, flavor, etc. This rules out categories where consumers' preferences hinge on dozens of different characteristics (such as ice cream).[20]

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

[18] 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.

[19] This definition of experience goods is broader than the one given by Nelson (1970), who focuses narrowly on consumers' learning about product quality. By contrast, I also allow for the possibility that consumers learn about their subjective tastes for specific products.

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

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.

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.

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 thirty-seven hours.[21]

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 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).

[21] 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.

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, such as 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 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

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.

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%.[22]

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.[23] 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 (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.

[22]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.)

[23]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].)

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 likelier to be accepted if it shares a given characteristic with the out-of-stock product than if it does not. This is true of nearly all product categories and characteristics.[24] Once more, some characteristics seem to loom larger in consumers' minds 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.

With only one exception, 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 statistically significant at the 1% level.[25]

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).[26] 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 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 reverse.

[24] 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)

[25] 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.

[26] Consumers often purchase the same product, or at least a product of the same brand, on consecutive trips (see Appendix Table 3).

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.

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. Suppose that these granola bars go out of stock on one occasion, 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 product 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; consumers may hold more accurate prior beliefs about their tastes for some characteristics than others. For instance, intuition suggests that granola bar buyers are more likely to learn about their preferences for brands or textures 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 produts' 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. Assume that, on one occasion, 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. Notice that 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 will learn 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 can be attributed exclusively to 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 then identify all successful curbside pickups of the focal consumer's preferred product *before* it went out of stock.[27] Of these

[27] 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

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 the stockout occurs.[28] 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 successfully pick up their preferred products before the stockout event), 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 focal or control consumer has made a substantial number of purchases before the stockout event, ranging from about ten to forty 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.[29] Now turn to consumers' purchases after the stockout event. Here,

Appendix Table 6.

[28]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.

[29]For the intent is to study consumers who, due to their past purchase histories, are presently unsure of their tastes for

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	Frac. of future purchases that share characteristic with sub, conditional on order outcome: Succesful pickup
		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)

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.

Brand aside, it is more difficult to judge whether consumers learn about other observable characteristics. The reason is that there are relatively few observations such that 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 for 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.

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 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.

the substitute's version of the characteristic.

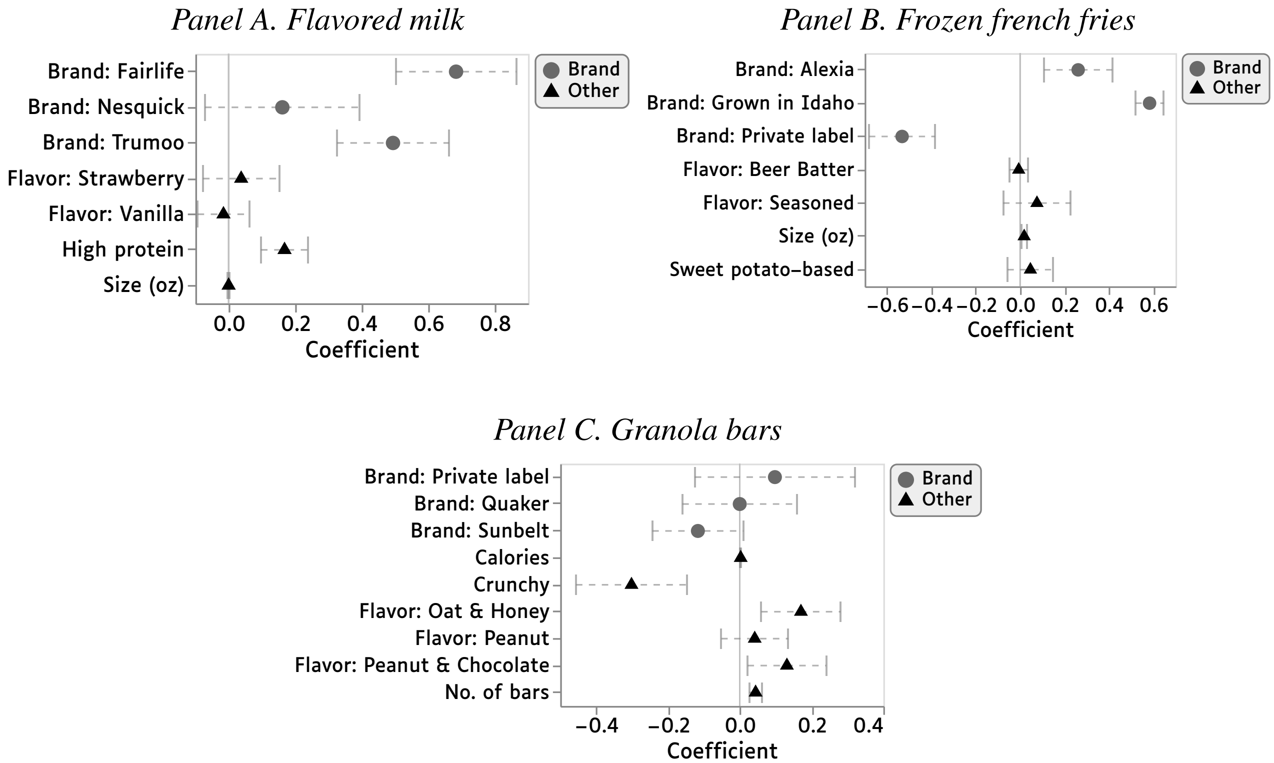

FIGURE 1 – DETERMINANTS OF RETAIL MARGINS

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.

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.[30] How do observable characteristics like brand, size, or flavor influence retail margins?

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

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

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.[31]

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

[30] 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.

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

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.

Concerning flavored milk and frozen french fries, the three largest coefficients (in absolute value) correspond to the brand dummies. This suggests that brand is a more important determinant of retail margins than are the other discrete characteristics. As for granola bars, the picture is more complicated. Although the coefficients associated with two of the three brand dummies are large, so too are the coefficients associated with some non-brand characteristics (particularly the dummy on crunchy texture).

It is more difficult to assess the continuous characteristics' influence on retail margins, as the estimated coefficients depend on the unit of measurement. Consider, therefore, the change in the predicted price 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 suggest that the characteristic of *brand* is among the primary determinants of retail margins in all three product categories.

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 a substitute from a high-margin brand that she has never bought 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. It also wants to ensure that the consumer is happy with the store's handling of the stockout (so that she does not reduce her future patronage).[32] And the latter objectives are likelier to be achieved if the store instead offers a substitute from a familiar, albeit

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

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 (a), the 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").[33]

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. Regarding (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 substitute. As to (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

[33] 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.

ordered good A, the optimal substitute is:

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

In this equation, $\Pr[\text{accept } s]$ denotes the probability that the consumer accepts s, given that she originally ordered good A.[34] 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.

A. The Model

Consider discrete choice among J_t goods/products at "time" t,[35] 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.[36] Besides brand, products are differentiated with respect to non-brand observable characteristics (such as texture or size). These are indexed by k.

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

[35] 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.

[36] 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.)

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}),[37] 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}).[38]

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, there is stronger descriptive evidence that consumers learn 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.[39]

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

[37] 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").

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

[39] 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 richer 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 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.)

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.[40] 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 ($v_{iB(j)}$) 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 v_{ib}.

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

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

with

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

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 the present one. The same is true of their decisions to accept or reject substitutes. For, whenever a consumer purchases a new brand for the first time (or accepts it as a substitute), she learns her true taste for that brand. This learning will enable her 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.

[40] 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.

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.[41] 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.[42]

B. *Estimation Method*

The task is to estimate the following objects:

1. The distribution of consumers' *prior expected* tastes μ_{ib} for each brand b
2. The distribution of consumers' *true* tastes v_{ib} for each brand b
3. The distribution of consumers' tastes β_{ik} for each non-brand characteristic k, along with the distribution of price coefficients α_i
4. Unobserved factors ξ_{jt} that influence demand for goods j at store/time t

Notice that heterogeneity in consumers' *true* tastes for a given brand b depends on two parameters. One is the degree of heterogeneity in consumers' prior expected tastes (σ_b^2), while the other is the informativeness of their priors (ι_b^2). Summing these two parameters yields the standard deviation of consumers' true tastes for a given brand:

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

This follows immediately from $v_{ib} \sim \text{Normal}(\mu_{ib}, \iota_b^2)$ and $\mu_{ib} \sim \text{Normal}(\mu_b, \sigma_b^2)$.

Now consider the parameters relating to products' non-brand observable characteristics (x_j) and prices (p_{jt}). Unlike their tastes for brands, which must be learned from experience, consumers innately know their tastes β_{ik} for non-brand observables k, as well as their price sensitivities α_i.[43]

[41] 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.

[42] 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.

[43] Customarily, α_i is interpreted as the marginal utiltiy of income (see Petrin [2002]). Here, however, I model consumers' demand *conditional* on making a purchase within the relevant product category. Hence, α_i is likely smaller in magnitude than the marginal utility of income.

Consequently, the parameters that determine the distributions of β_i and α_i across the population of consumers i are equivalent to those in workhorse demand systems (such as Berry, Levinsohn, and Pakes [1995]).

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 unobservable demand factor is store-level promotional activities, like inclusion in a flyer or placement in a prominent location (a.k.a. "endcap"). In the utility specification, such shocks are represented by the term ξ_{jt}.[44]

To recover the unobserved demand factors ξ_{jt}, I adopt 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 directly influence consumers' utility, this pricing function also depends on a set of excluded instruments. I employ products' wholesale costs for this purpose, as they are correlated with retail prices, but plausibly uncorrelated with store-level promotional activities. Turning to the second step, I include the residuals from the reduced-form pricing equation (denoted by $\tilde{\xi}_{jt}$) as explanatory variables in the latent utility function. Practically speaking, this amounts to replacing ξ_{jt} in equation (3) with $\lambda\tilde{\xi}_{jt}$ (where λ is a scaling parameter to be estimated). See Appendix C for a more detailed discussion of the control function.

With the control function in hand, the parameters that govern consumers' utility and learning are obtained via maximum simulated likelihood estimation. Appendix C provides details.

Identification.—Although formal identification of the model's parameters is beyond the scope of this paper, I will briefly sketch the intuition here. Because there is already a large literature on the identification of random coefficients in the absence of learning (see Fox et al. [2012] and Iaria and Wang [2024]), I will focus on the parameters that pertain to consumers' learning.

First consider μ_b, which corresponds to consumers' mean prior expected tastes for brand b (as well as their mean *true* tastes). This parameter is identified as follows. 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 and 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 consumer's prior expected tastes for brand b. This parameter is identified by variation in how many purchases consumers make *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 a given brand b. 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

[44]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.)

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 taste 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 is inversely related to the informativeness of consumers' prior probability distributions on their tastes for brand b. It is identified by the relationship between two factors: (i) the number of orders placed before consumer first purchase one of the brand's products, and (ii) the frequency with which they purchase the brand's products thereafter. Factors (i) and (ii) relate differently if consumers' prior expected taste for b closely resemble their true tastes (i.e., if $\mu_{ib} \approx \nu_{ib}$) than if their prior expected tastes diverge from their true tastes (i.e., if $|\mu_{ib} - \nu_{ib}| \gg 0$).

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.[45] 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 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.

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 record the UPC and price of the item that was ultimately purchased. These data also enable me to infer the UPCs and prices of goods that the consumer did *not* purchase as follows. First, 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

[45] 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.)

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).[46] 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 one, 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.[47] 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.[48]

Initial Conditions Problem.—Some consumers will 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?[49]

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.

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

[47] 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.

[48] 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.

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

6. Estimation Results

In this section, I report the results from estimating the model 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 them below.

Table 5 presents the parameter 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' prior expected tastes for the mainstream brands manifest greater heterogeneity than do their 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. For most such characteristics k, I do not attempt to model heterogeneity in consumers' preferences. Rather, I recover solely a fixed coefficient β_k that measures consumers' mean tastes for the relevant characteristic. The only 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 other flavors to chocolate.

Turn next to the random price coefficient. I assume that α_i is distributed truncated normal, with shift parameter α, scale parameter σ_α^2, and one-sided truncation of the left tail so that the support is $(0, \infty)$.[50] Notice that the estimated scale parameter (σ_α) greatly exceeds the estimated shift parameter (α). This suggests that consumers evince highly heterogeneous sensitivities to price.

Finally, consider the coefficients on the control function and on in-person rejection. 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, starting in September 2021, consumers

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

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

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		
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. See Appendix C for details.

[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).

were able to accept or reject substitutes remotely (using the store's app or website). Intuitively, this should 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 occuring 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 almost nothing. 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"—seeks to provide the closest available substitute for the out-of-stock product.[51] This affords two key advantages. First, the consumer will probably accept the substitute. This means that the store is likely to earn the substitute's retail margin. Second, the consumer will probably feel satisfied with the store's handling of the stockout. The store is, therefore, unlikely to lose any of her future patronage as a direct result of the substitution.

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), conditional on the substitute's being 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. What she learns may influence her subsequent purchases and, ultimately, the store's future profits.

To what extent (if any) could the store increase profits by attending to these additional determinants of profits? I face an empirical challenge as I seek to answer this question: although both stockout substitutions and consumer attrition are observable in the data, I cannot recover the relationship between the two. In the first place, stockout substitutions are unlikely to be a first-order determinant of the consumer's future expenditures. Other factors, such as the intensity of competition faced by a specific store location, probably play a much larger role. In the next place, consumers who experience

[51] Recall that the choice of substitute is left to store workers, who asked to "use their best judgment" in selecting a substitute. (See footnote **??** in Section 1 for details.)

a stockout substitution within the focal product category usually experience stockout substitutions in *other* product categories at the same time! 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.[52] 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.

My response to this empirical challenge proceeds as follows. I begin by obtaining upper bounds on the returns to steering consumers' learning. To do so, I temporarily assume that the store's choice of substitute does not affect consumer attrition. This enables me to characterize a conditionally optimal stockout substitution policy—hereafter, the "steering" policy—that maximizes the present-discounted value of expected profits (holding attrition constant). Then I compare the store's present-discounted value of expected profits under the "steering" policy with that under the "baseline" policy (still holding attrition constant). This comparison yields an upper bound on the returns to steering consumers' learning.

In the second step of my counterfactual analysis, I identify the stockouts with the largest upper bounds on the returns to steering consumers' learning. The intuition is as follows: if there exist any stockouts where it is optimal for the store to steer consumers' learning, these stockouts are likely to be among them. It emerges that most of the potential gains from steering consumers' learning are concentrated in cases where the consumer has *only* purchased the "budget" brand (i.e., Sunbelt) on past shopping trips. By offering a substitute from the more popular of the "mainstream" brands (namely, Quaker), the store can perceptibly increase its expected future profits from these consumers—provided, again, that attrition is unaffected by the store's choice of substitute.

In the third (and final) step of my counterfactual analysis, I relax the assumption that attrition is independent of the store's choice of substitute. Then, focusing on the stockouts with the highest potential returns to steering consumers' learning (i.e., when the consumer has only purchased the budget brand before), I ask whether the gains from steering consumers' learning are likely to exceed the losses from (potentially) heightened attrition.

A. *Simulation Approach*

Simulation proceeds as follows. First, I characterize the "steering" substitution policy, which is designed to maximize the store's present-discounted value of expected profits while holding attrition constant. Here, I only leverage information that is availabilities to the store at the time of the stockout substitution—that is, data from shopping trips *before* the stockout event. And second, I compare the

[52]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.

present-discounted value of expected profits under the "steering" policy with that under the "baseline" policy (still holding attrition constant). There, I leverage the entirety of the data.

Characterizing the Steering Substitution Policy.—Under the steering policy, the store will offer the substitute that maximizes the present-discounted value of expected profits (holding attrition constant). 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 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 allow consumers to endogenously learn about additional brands on shopping trips *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.[53]

Of course, this procedure reflects future profits under just one possible future state of the world. Accordingly, I repeat the entire procedure—synthesizing data and computing choice probabilities—several times in order to "integrate" over various potential 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 compute 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 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 store's present-discounted value of expected profits conditional on attrition remaining constant.) 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. So far

[53]This is roughly equivalent to a 0.93 real annual discount rate.

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, may have exclusively purchased the highest-margin brand (namely, 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 offering a substitute from the brand with the highest retail margins (and mean utility): Quaker.[54] I will henceforth refer to stockouts of this description as "budget buyer" stockouts, and other 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 much smaller fraction of the steering substitutes are marked down than their baseline counterparts.[55] The steering substitutes also tend to consist of larger packages than do their baseline counterparts (14.9 bars versus 8.3, respectively).[56] Finally, regarding 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, the steering policy usually proposes a Quaker- or Nature Valley–branded substitute.[57]

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—perhaps because it affords high retail margins, or because it introduces the consumer to a high-margin brand, or both. Note 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

[54]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.)

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

[56]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.

[57]93.8% and 4.1% of baseline and steering substitutes are Sunbelt-branded, respectively.

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, conditional on consumer attrition remaining equal to that in the data (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.

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 out-of-stock product's brand.[58]

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. But if she accepts, the store's choice of substitute may influence her learning and, consequently, 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 PDV of expected future profits by \$0.22 on average (conditional on acceptance). This represents a 1.4% increase over the baseline

[58] 99.0% and 64.6% of baseline and steering substitutes, respectively, share the out-of-stock product's brand.

present-discounted value of future profits (conditional on acceptance) of \$15.75. 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 so dramatically 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 with respect to the "steering" and "mainstream buyer" stockouts: \$0.70 and \$0.79, respectively. However, this similitude masks an important difference between the two stockout types. Concerning the "budget buyer" stockouts, the gains under the steering substitution policy reflect increases in both (i) present-trip margins and (ii) discounted future-trip profits. For the "mainstream buyer" stockouts, by contrast, the gains under the steering policy only reflect (i).

What About Attrition?—Should the store adopt the "steering policy?" Simulations suggest that the "steering" policy would increase the present-discounted value of expected profits by about \$0.70 per consumer (holding attrition constant). So, unless the "steering" policy increases attrition-related losses per consumer by more than \$0.70, the "steering" policy would increase profits compared to the baseline.

Intuition suggests that the "steering" policy is unlikely to increase attrition by anything near this amount. As mentioned previously, the store's handling of stockout substitutions is probably not a first-order determinant of where consumers choose to shop. Furthermore, the "steering" and "baseline" substitutes are fairly close in price (with the former's price exceeding the latter's by an average of \$0.33 and \$0.07 for the "budget buyer" and "mainstream buyer" stockouts, respectively). It seems unlikely that such a modest price difference would materially diminish consumers' satisfaction with the store's handling of the stockout substitution.

If the store remained concerned that the "steering" policy would increase consumer attrition, it could offer consumers a "substitution discount" when they suffer stockout substitutions. This discount could be set at an amount smaller than the expected increase in profits under the "steering" policy (compared to its "baseline" counterpart).

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 both the out-of-stock product and the entirety of the consumer's past purchases are of the budget Sunbelt brand; and "mainstream buyer" stockouts, where either the out-of-stock product or a previous purchase are of the mainstream Nature Valley or Quaker brands. Why is this distinction so important?

In what follows, I explore the sources of 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 because, 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 for two reasons. First, the consumer probably has higher tastes (both expected and actual) for brands that she has previously purchased than for brands that she has not. Thus, together with the brand of the out-of-stock product, the set of previously-purchased brands helps predict whether the consumer will accept substitutes of various brands. And second, 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 that 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 among each brand's products, by which I mean the following: if the store *must* 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 must select a stockout substitute on behalf of 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). In other words, 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

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).

the consumer has previously purchased. (Results for combinations of [a] and [b] with fewer than 50 observations are relegated to the Appendix. I also omit the 73 observations in which one of the brands is completely out of stock.[59])

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 solely 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

[59]More specifically, these are observations where the brand's top-selling products—i.e., those included in estimation—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 (holding consumer attrition constant). 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.

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.

C. Counterfactual Results: Flavored Milk and Frozen French Fries

In this subsection, I briefly summarize the counterfactual results for the other two product categories: flavored milk and frozen french fries. Recall that the demand estimates suggest that consumers learn less about these product categories than they do about granola bars. Intuively, the gains from steering consumers' learning should, therefore, be smaller for these categories than for granola bars. This intuition is supported by the counterfactual simulations, which are presented in Appendix Tables 11 to 13. 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 suggest the that the returns to steering consumers' learning depend on the amount of learning within the relevant product category, as well as on individual consumers' purchase histories.

This paper makes two main contributions, one on the demand side of the market and the other on the supply side. Regarding the former, I leverage quasi-experimental variation in the precise timing of stockouts to (i) provide descriptive evidence of stockout substitutions' influence on consumer learning and (ii) help identify consumer learning within a model of differentiated products demand. As for the latter, I leverage unique features of my environment to characterize the optimal supply-side strategy to steer consumers' learning. (To my knowledge, this study is the first to do so.)

More broadly, my findings underline the need for further research about how firms steer consumers' learning online. This is because firms steer consumers' learning to maximize profits, not with consumers' welfare in mind. In the context of curbside pickup, such steering has negligible effects on consumers' welfare; someone's quality of life will not change if a stockout substitution results in her trying out a high-margin brand of granola bars or chocolate milk. But in other online contexts, the welfare impact may be substantial. Take the case of web browsers, for instance. 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). Another example concerns online shopping, where Google exploits its dominance in web search to promote its eponymous shopping service (Raedts and Evans 2024). Of course, many of the affected consumers are probably 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 might try to quantify the welfare effects of tech giants' steering of consumer learning in relation to browsers, online shopping, and other areas.

References

Ackerberg, Daniel A. "Advertising, Learning, and Consumer Choice in Experience Good Markets: An Empirical Examination". Publisher: Wiley Online Library, *International Economic Review* 44, no. 3 (2003): 1007–1040.

Acosta. "New Acosta Report Highlights Top Influencers Driving Retailer Traffic". PR Newswire, Dec. 6, 2017. prnewswire.com/news-releases/new-acosta-report-highlights-top-influencers-driving-retailer-traffic-300567760.html.

Anand, Bharat N., and Ron Shachar. "Advertising, the Matchmaker". *The RAND Journal of Economics* 42, no. 2 (June 2011): 205–245.

Arteaga, Cristian, et al. "xlogit: An Open-Source Python Package for GPU-Accelerated Estimation of Mixed Logit Models". Publisher: Elsevier, *Journal of Choice Modelling* 42 (2022): 100339.

Barwick, Panle Jia, et al. "From Fog to Smog: The Value of Pollution Information". Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, *American Economic Review* 114, no. 5 (2024): 1338–1381. Visited on 09/14/2024. https://www.aeaweb.org/articles?id=10.1257/aer.20200956.

Berry, Steven, James Levinsohn, and Ariel Pakes. "Automobile Prices in Market Equilibrium". *Econometrica* 63, no. 4 (1995): 841–890.

Berry, Steven T., and Philip A. Haile. "Foundations of Demand Estimation". In *Handbook of Industrial Organization*, ed. by Kate Ho, Ali Hortaçsu, and Alessandro Lizzeri, 4:1–62. Elsevier, 2021.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen. "Calorie Posting in Chain Restaurants". Publisher: American Economic Association, *American Economic Journal: Economic Policy* 3, no. 1 (2011): 91–128. Visited on 09/14/2024. https://www.aeaweb.org/articles?id=10.1257/pol.3.1.91.

Brick Meets Click and Mercatus. "February U.S. eGrocery Sales Total $7.9 Billion, Down 10% versus Year Ago". Brick meets click, Mar. 13, 2024. Press Release. https://www.brickmeetsclick.com/stuff/contentmgr/files/0/b33b7d7f9604fb8a97b9678ec53165a0/files/bmc_eshopper_mar_2024_press_release_final_with_graphic.pdf.

Che, Hai, Tülin Erdem, and T. Sabri Öncü. “Consumer Learning and Evolution of Consumer Brand Preferences”. *Quantitative Marketing and Economics* 13, no. 3 (Sept. 2015): 173–202.

Ching, Andrew T. “A Dynamic Oligopoly Structural Model for the Prescription Drug Market After Patent Expiration*”. *International Economic Review* 51, no. 4 (Nov. 2010): 1175–1207.

– . “Consumer Learning and Heterogeneity: Dynamics of Demand for Prescription Drugs After Patent Expiration”. Publisher: Elsevier, *International Journal of Industrial Organization* 28, no. 6 (2010): 619–638.

Daljord, Øystein. “Durable Goods Adoption and the Consumer Discount Factor: A Case Study of the Norwegian Book Market”. Publisher: INFORMS, *Management Science* 68, no. 9 (2022): 6783–6796. Visited on 08/21/2024. https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2021.4208?casa_token=r-DzVGHlq2kAAAAA:VecFvOiwVnxmW0VrxXjyMH0atSanyts-hhI33AmnexqXm1I4o5iRdQB6zV5l-OohuR1ckhpD3Cw.

Erdem, Tülin, and Michael P. Keane. “Decision-Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets”. Publisher: INFORMS, *Marketing Science* 15, no. 1 (1996): 1–20.

Erdem, Tülin, Michael P. Keane, and Baohong Sun. “A Dynamic Model of Brand Choice When Price and Advertising Signal Product Quality”. Publisher: INFORMS, *Marketing Science* 27, no. 6 (2008): 1111–1125.

Fox, Jeremy T., et al. “The Random Coefficients Logit Model Is Identified”. Publisher: Elsevier, *Journal of Econometrics* 166, no. 2 (2012): 204–212.

Gandhi, Amit, and Jean-François Houde. “Measuring Substitution Patterns in Differentiated-Products Industries”. Working paper, 2023. jfhoude.econ.wisc.edu/research-in-progress/.

Harris-Lagoudakis, Katherine. “Online Shopping and the Healthfulness of Grocery Purchases”. *American Journal of Agricultural Economics* 104, no. 3 (May 2022): 1050–1076. ISSN: 0002-9092, 1467-8276, visited on 06/30/2024. https://doi.org/10.1111/ajae.12262. https://onlinelibrary.wiley.com/doi/10.1111/ajae.12262.

Hastings, Justine S., and Jeffrey M. Weinstein. “Information, School Choice, and Academic Achievement: Evidence from Two Experiments”. Publisher: MIT Press, *The Quarterly Journal of Economics* 123, no. 4 (2008): 1373–1414. Visited on 09/14/2024. https://academic.oup.com/qje/article-abstract/123/4/1373/1933172.

Hollister, Sean. “Microsoft Now Thirstily Injects a Poll When You Download Google Chrome”. The Verge, Oct. 24, 2023. theverge.com/23930960/microsoft-edge-google-chrome-poll-why-try-another-browser.

Iaria, Alessandro, and Ao Wang. "Real Analytic Discrete Choice Models of Demand: Theory and Implications". Publisher: Cambridge University Press, *Econometric Theory* (2024): 1–49. Visited on 09/29/2024. https://www.cambridge.org/core/journals/econometric-theory/article/real-analytic-discrete-choice-models-of-demand-theory-and-implications/E7E128A1BA960367FB6C1AF6DAFC4DF4.

Jessoe, Katrina, and David Rapson. "Knowledge Is (less) Power: Experimental Evidence from Residential Energy Use". Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, *American Economic Review* 104, no. 4 (2014): 1417–1438. Visited on 09/14/2024. https://www.aeaweb.org/articles?id=10.1257/aer.104.4.1417.

Kim, Kyoo il, and Amil Petrin. "Control Function Corrections for Unobserved Factors in Differentiated Product Models". Working paper, 2019. sites.google.com/site/kyookim/.

Kling, Jeffrey R., et al. "Comparison Friction: Experimental Evidence from Medicare Drug Plans". Publisher: MIT Press, *The Quarterly Journal of Economics* 127, no. 1 (2012): 199–235. Visited on 09/25/2024.

Krasnoff, Barbara. "How to change your default browser in Windows 11". The Verge, Apr. 15, 2022. theverge.com/22714629/windows-11-microsoft-browser-edge-chrome-firefox.

Mastromonaco, Ralph. "Do environmental right-to-know laws affect markets? Capitalization of information in the toxic release inventory". Publisher: Elsevier, *Journal of Environmental Economics and Management* 71 (2015): 54–70.

Nelson, Phillip. "Information and Consumer Behavior". *Journal of Political Economy* 78, no. 2 (Mar. 1970): 311–329.

Osborne, Matthew. "Consumer Learning, Switching Costs, and Heterogeneity: A Structural Examination". Publisher: Springer, *Quantitative Marketing and Economics* 9 (2011): 25–70.

Pakes, Ariel. "Dynamic Structural Models, Problems and Prospects". Advances in Econometrics. Sixth World Congress, Cambridge University Press, 1994.

Petrin, Amil. "Quantifying the Benefits of New Products: The Case of the Minivan". *Journal of Political Economy* 110, no. 4 (Aug. 2002): 705–729.

Raedts, Elske, and Simone Evans. "Google Shopping: Self-Preferencing Can Be Abusive". Stibbe, Feb. 10, 2024. stibbe.com/publications-and-insights/google-shopping-self-preferencing-can-be-abusive.

Shin, Sangwoo, Sanjog Misra, and Dan Horsky. "Disentangling Preferences and Learning in Brand Choice Models". *Marketing Science* 31, no. 1 (Jan. 2012): 115–137. ISSN: 0732-2399, 1526-548X, visited on 09/28/2024. https://doi.org/10.1287/mksc.1110.0680. https://pubsonline.informs.org/doi/10.1287/mksc.1110.0680.

Train, Kenneth E. *Discrete Choice Methods with Simulation*. Cambridge University Press, 2009.

Young, Liz. "Never Mind the Delivery, More Online Consumers Are Turning to Store Pickup". *The Wall Street Journal* (July 14, 2023). `https://www.wsj.com/articles/never-mind-the-delivery-more-online-consumers-are-turning-to-store-pickup-a9683449`.

Zeyveld, Andrew. "Preferences among Unpurchased Goods in Differentiated Products Demand Systems". Working Paper (2024). `zeyveld.github.io/assets/pdf/unpurchased-goods.pdf`.

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 ($p_{i,\text{OOS}}$).[60]

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

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

[60] 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).[61] 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

[61]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)

		No. of purchases		Frac. of future purchases that share characteristic with sub, conditional on order outcome	
Characteristic	Obs.	Before stockout	After stockout	Suffer substitution	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")

		No. of purchases		Frac. of future purchases that share characteristic with sub, conditional on order outcome	
Characteristic	Obs.	Before stockout	After stockout	Suffer substitution	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

$$\mathrm{E}[\nu_{iB(j)} \mid \mathcal{I}_{it}] = \underbrace{\mu_{iB(j)}}_{\substack{\text{prior expected}\\ \text{taste}}} + \underbrace{(\nu_{iB(j)} - \mu_{iB(j)})\, 1[B(j) \in \mathcal{I}_{it}]}_{\substack{\text{learning "correction" (if brand}\\ \text{was previously purchased)}}} \tag{7}$$

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 $\nu_{iB(j)}$ differs from her prior expected taste $\mu_{iB(j)}$.

In order to take equation equation (7) 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, $\big(1[B(j) = 1], \dots, 1[B(j) = B]\big)^\intercal$; and

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

This is true because

$$\begin{aligned}
\mu_{iB(j)} &= \sum_{b=1}^{B} 1[B(j) = b] \cdot \mu_{ib} \\
&= \Big(1[B(j) = 1] \quad \cdots \quad 1[B(j) = B]\Big) \cdot \begin{pmatrix} \mu_{i1} \\ \vdots \\ \mu_{iB} \end{pmatrix}
\end{aligned} \tag{8}$$

The "learning correction" $(\nu_{iB(j)} - \mu_{iB(j)})$ 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, $\big(1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}], \dots, 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}]\big)^\intercal$, 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

$$\begin{aligned} v_{ib} - \mu_{ib} &= \sum_{b=1}^{B} 1[B(j) = b \text{ and } b \in \mathcal{I}_{it}](v_{ib} - \mu_{ib}) \\ &= \Big(1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}] \quad \cdots \quad 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}]\Big) \begin{pmatrix} v_{i1} - \mu_{i1} \\ \vdots \\ v_{iB} - \mu_{iB} \end{pmatrix} \end{aligned} \tag{9}$$

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

$$w_{jt} \equiv \begin{pmatrix} \Big(1[B(j) = b]\Big)_{b=1}^{B} \\ \Big(1[B(j) = 1 \text{ and } 1 \in \mathcal{I}_{it}], \cdots, 1[B(j) = B \text{ and } B \in \mathcal{I}_{it}]\Big) \\ x_j \\ p_{jt} \\ \xi_{jt} \end{pmatrix}$$

while the complete set of parameters can be written as

$$\chi_i \equiv \begin{pmatrix} (\mu_b)_{b=1}^{B} \\ (v_b - \mu_b)_{b=1}^{B} \\ \beta \\ \alpha \\ \gamma \end{pmatrix}$$

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.[62] 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 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:

$$P_i \equiv \int (P_i \mid \chi) f_\chi(\chi) d\chi \tag{10}$$

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 $(\nu_{ib} - \mu_{ib})$'s],

[62] 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.

etc.)

As I previously mentioned, equation equation (10) 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:

$$\check{P}_i = \frac{1}{R} \sum_{r=1}^{R} \left(P_i \mid \chi^r \right) \tag{11}$$

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;

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

Endogenous Prices and the Control Function.—Recall that equation (3) addresses endogeneity in prices through the inclusion of demand-shock terms ξ_{jt}. Here I discuss the recovery of those shocks. Before I can proceed, I must introduce store-location subscripts $l \in \mathcal{L}_t \equiv \{1, \ldots, L_t\}$ in order to accommodate variation in prices between individual store locations at a given time.[63] Minding this additional notation, the recovery of the demand shocks proceeds as follows.

I employ the control function approach proposed by Kim and Petrin (2019). Suppose that (i) prices p_{jtl} are a function of observable characteristics x_j, along with the unobservable demand factor ξ_{jtl} and a vector of excluded instruments z_{jtl}; and that (ii) prices are additively separable in ξ_{jtl}. In other words, the reduced form of price takes the form

$$p_{jtl} = g(x_j, z_{jtl}) + h_j(\xi_{jtl}) \tag{12}$$

for each product j, time t, and store location l. Then, under mild monotonicity assumptions, the variable $v(\xi_{jtl})$ is one-to-one with ξ_{jtl}. And $v(\xi_{jtl})$, in turn, can be estimated as the regression residual of equation (12).

My estimation of equation (12) adopts the following expedients. In the role of excluded instruments, I employ Hausman IVs. These consist of a product's average price across all *other* store locations at the time in question. That is, for each good j, time t, and store location l, the excluded instrument is computed as $z_{jtl} \equiv \frac{1}{L-1} \sum_{l' \in \mathcal{L}_t \setminus \{l\}} p_{jtl'}$. (As a robustness check, the appendix presents estimates with

[63] Pedantically, both the price variable p_{jt} and the demand shock ξ_{jt} should always include a store-location subscript l (becoming p_{jtl} and ξ_{jt}, respectively). I suppress this subscript elsewhere in the interest of readability.

two alternative instruments: the "differentiation IVs" proposed by Gandhi and Houde [2023], as well as products' marginal costs.) As for the functional form of g, I assume it to be linear.[64] Accordingly, I estimate equation (12) via ordinary least squares.

Aside from the own-product regression residuals $v(\xi_{jtl})$ of equation (12), my control function includes two additional terms, which reflect that the sum of *other* products' regression residuals within a given time t and location l may also be informative of unobserved determinants of demand for the product (Pakes 1994, as cited in Kim and Petrin 2019). The first of these terms is the sum of residuals for the other products j' sold under the same brand as j; that is, $\sum_{j'\neq j, B(j')=B(j)} v(\xi_{j'tl})$. And the second of these terms is the sum of residuals for the other products j'' sold under different brands from j, that is $\sum_{j''\neq j, B(j'')\neq B(j)} v(\xi_{j''tl})$. Thus the control function used in estimation takes the form

$$\xi_{jtl} = \lambda_1 v(\xi_{jtl}) + \lambda_2 \sum_{j'\neq j, B(j')=B(j)} v(\xi_{j'tl}) + \lambda_3 \sum_{j''\neq j, B(j'')\neq B(j)} v(\xi_{j''tl})$$

Change in Accept/Reject Procedure.—Recall that the context of consumers' accept/reject decisions depends on the pickup date. 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 psychological cost of rejecting a substitute,[65] 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

$$\mathrm{E}[u_{ist} \mid \mathcal{I}_{it}] \geqslant u_{i0t} - \gamma \cdot 1[\text{reject in-person}], \tag{13}$$

where the parameter γ measures the psychological cost of rejecting a substitute in-person.

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

[64] More flexible specifications are unsuitable due to the small number of products within each consumer goods category. If I estimated equation (12) nonparametrically, the interaction terms would identify individual products. The regression residuals would then reflect only unobserved demand factors at the market and the product-market levels, not at the product level.

[65] When accepting or rejecting in-person, consumers might have felt social pressure to accept the substitute.

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).

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 refrigerated (and thus cannot be placed on endcaps).

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 Appendix C 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).

E. Additional Counterfactual Simulations

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

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, conditional on consumer attrition remaining equal to that in the data (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 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, conditional on consumer attrition remaining equal to that in the data (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.