New-Product Diffusion under Uncertainty: Evidence from Rollout, Testing, and Learning

Hongzhang Xie

November 2025

Note for Admissions Committees. This writing sample is a single-authored draft derived from a broader research project conducted under the supervision of Professor Tomomichi Amano at Harvard Business School. The analyses, interpretations, and writing presented in this document are the applicant's own work; any remaining errors are the applicant's own.

Latest version available at:

https://drive.google.com/file/d/10FvHS047CzDblPePaa62foy6SULMglzA/view?usp=sharing

Abstract

This paper studies how grocery retailers manage uncertainty in new product introductions through staged roll-outs. Using Nielsen Retail Scanner data (2006–2019) matched to local demographics, we document three stylized facts and interpret them through a dynamic learning framework. First, retailers differ systematically in adoption timing: retailers with larger store networks release national new products earlier, introduce more items, and accept higher early failure rates, while smaller retailers tend to adopt later. Second, within a retailer, new products are rarely launched network-wide; instead, they are introduced in a limited set of stores and then either expanded or discontinued. Stronger early performance in these initial stores predicts subsequent expansion, while weaker performance predicts discontinuation, consistent with retailers learning from early internal sales signals. Third, the returns to experimentation increase with retailer scale: testing costs are concentrated in the initial pilot stores, while the payoff from identifying a winner increases with the retailer's capacity to scale. This scale effect rationalizes why larger retailers test earlier and more aggressively, whereas smaller retailers delay adoption to infer product quality from external signals. Finally, these strategies may have distributional implications. Early tests are disproportionately conducted in higher-income areas, so the signals guiding expand-or-drop decisions may overweight affluent demand. This informational filter can shape which innovations survive and spread, potentially delaying or limiting access in lower-income neighborhoods.

1 Introduction

Firms regularly introduce new products to satisfy consumers' demand for variety and to replace items that have become outdated. Yet the launch of a genuinely new product—especially one that has never been sold in the U.S. market—entails substantial risk: 25% of new SKUs are no longer purchased one year after introduction, and 40% disappear within two years (Victory et al., 2021; Gielens and Steenkamp, 2007). This paper studies how grocery retailers manage this uncertainty through staged roll-outs. Retailers often start in a limited set of stores and then expand or discontinue products as information accumulates. We ask two related questions. First, when do retailers adopt nationally released new products, and how do they adjust store coverage over time? Second, how do these risk-management strategies shape diffusion across stores, retailers, and neighborhoods, and what are the implications for consumers across income groups?

We address these questions using Nielsen Retail Scanner (RMS) data from 2006–2019, matched to county-level household income from the American Community Survey (ACS). The data allow us to track national new products from their first national sale through their diffusion across retailers' store networks and neighborhoods. We document three empirical patterns in retailers' adoption, testing, and subsequent spread decisions. We interpret these patterns through the lens of a dynamic learning framework. In the framework, retailers choose how many stores to expose to a new product and update beliefs about its quality using both inside and outside information.

First, retailers differ systematically in how quickly they adopt national new products, and early adoption is closely related to retailer scale. Earlier adopters tend to operate larger store networks, generate higher revenue, and adopt many more unique items. For example, the four fastest-adopting retailers adopt roughly 250,000 unique new products over the sample period. This is more than three times the 75,000 adopted by the ten slowest adopters. Early adopters also face higher early discontinuation rates: 21.6% of adopted products are discontinued within three months, compared to 15.9% for later adopters. These differences extend to the store level. Taken together, these patterns are consistent with the interpretation that earlier adoption is associated with more intensive experimentation, not only the mechanical implication of operating more stores.

Second, within retailers, products are rarely introduced in all stores at once. During the first three months, 91% of new products appear in fewer than 10% of a retailer's stores. Many items therefore begin in a limited subset of locations. Early sales performance in these initial stores is predictive of later outcomes. Products with stronger early performance tend to reach a larger share of stores over time. Weaker performers are more likely to be discontinued or to remain confined to a narrow set of locations. These patterns are consistent with retailers using early performance information when deciding whether to expand or exit (e.g., Ferreira and Mower, 2023; Cheung et al., 2017; Hitsch, 2006; Bronnenberg and Mela, 2004), although other operational and demand factors may also matter (e.g., Amano and Tamayo, 2025; Aparicio and Simester, 2022).

Third, we find evidence consistent with learning from external signals generated by other retailers and with returns to experimentation increasing in retailer scale. Retailers that adopt later are more likely to introduce a product when its early national performance is strong, even after controlling for the extent of early testing and product-module fixed effects. At the same time, scale shapes incentives to generate information internally. Testing can be done in a small number of stores, so the direct cost of producing informative signals need not rise one-for-one with network size. By contrast, the gains from identifying a successful product can be realized over many more stores in a larger network. This logic helps rationalize why large retailers often test earlier and more broadly, while smaller retailers may place greater weight on information generated by others.

These roll-out and learning strategies can have distributional implications because they interact with the geography of income. New products are initially tested in only a subset of stores, and these early-testing stores are disproportionately large-format locations in higher-income counties. Within the same retailer–state group, stores in the earliest adoption wave are located in areas where median household income is about \$4,000–\$5,000 higher than that of later-adopting stores. As a result, the early signals guiding spread and discontinuation decisions may place disproportionate weight on demand realized in higher-income neighborhoods. While such spatial patterns can serve as valuable predictors of new-product success (Garber et al., 2004), reliance on them reinforces the uneven distribution of product innovations and availability documented in prior literature (e.g., Jaravel, 2019; Handbury and Weinstein, 2015; Becerril-Arreola et al., 2021). It motivates examining how retailers' learning-based roll-out decisions can shape the distribution of access to successful new products.

To interpret these empirical patterns, we develop a dynamic learning framework in which retailers choose how many stores to expose to a new product while updating beliefs about its quality using both inside and outside signals. Retailers face store-level introduction costs and can discontinue products that are deemed unprofitable. The model highlights how differences in retailer scale, the precision of inside signals, the availability of outside information, and testing costs can generate heterogeneous test-versus-wait strategies. The framework also helps connect observed roll-out behavior to incentives and information.

The remainder of the paper is organized as follows. Section 2 describes the RMS and ACS data, the construction of the analysis sample, and key variables, including the definition of national new products and measures of adoption timing, spread, and failure. Section 3 presents descriptive evidence on retailers' new-product strategies and staged roll-outs. It documents heterogeneity in adoption timing and scale across retailers, differences between earlier- and later-adopting stores within chains, and the prevalence and dynamics of test-then-spread patterns within retailer–state networks. Section 4 assembles evidence on learning and mechanisms. It documents how early performance predicts subsequent expansion and discontinuation within retailer–state groups, how larger networks expand higher-performing products to more stores in absolute terms, and how early national performance predicts adoption by later adopters. It then develops a conceptual test-versus-wait framework and discusses potentially confounded mechanisms. Section 5 develops the dynamic learning model and reports simulation results that clarify how retailer scale and information flows jointly shape experimentation, diffusion, and failure. Section 6 discusses implications for consumers, firms, and policy, with a focus on how information generated in higher-income neighborhoods can shape access to new products across income groups. Section 7 concludes.

2 Data

Our primary data source is the Nielsen Retail Scanner (RMS) dataset for the period 2006 to 2019. The RMS data provides weekly information on prices, quantities sold, and store characteristics collected from point-of-sale systems of more than 90 retail chains across the United States. We also use data from the 2010–2015 American Community Survey (ACS) to identify demographic characteristics of the counties in which stores are located. Using each store's ZIP code, we match and obtain five-year average measures such as median household income. In robustness checks, we additionally use ACS data from 2005–2010 and 2015–2020.

Products. We treat each Universal Product Code (UPC) as a distinct product. To identify new products, we classify all UPCs that appear in the RMS data in 2006 as "old products," and we treat

UPCs that first appear in the RMS data in 2007 or later as new products. We define the national new product release time as the week in which a new product is first observed in the RMS data. Unless otherwise noted, our analysis focuses on all new products released between 2007 and 2019, excluding private label products.

Retailers and Stores. We focus exclusively on grocery retailers within the RMS data. We treat each store ID in the RMS data (store_code_uc) as a distinct store and each retailer ID (retailer_code) as a distinct retailer. We retain only stores that record positive sales every year from 2006 to 2019 (hereafter referred to as "target stores"). To define the relationship between stores and retailers, we use the ownership structure observed in 2019 and restrict the sample to retailers that own at least one target store. The final dataset includes 41 retailers and 5,940 stores. Detailed summary statistics are reported in Section 3.2, Table 2.

New Product Adoption Wait Time. We define a retailer's national wait time as the number of weeks between the week a product first appears in the RMS data and the week the retailer first sells it. Retailers that adopt a product shortly after its national release typically lack sufficient time to observe its performance at other retailers, thereby facing a higher risk of product failure. We refer to such instances as the retailer "adopted a national new product."

Selecting the threshold for this definition involves a trade-off. If the window is too short, the measure may be confounded by logistical delays and internal operational processes. Conversely, if the window is too long, retailers may have already adjusted their decisions based on external information. We classify products adopted within 3 months (12 weeks), 6 months (24 weeks), and 1 year (48 weeks) as 3-month, 6-month, and 12-month national new product adopts, respectively. Products adopted more than one year after their national release are not considered national new products, as retailers would have had sufficient time to observe the product's true quality from external information.

Retailer and Store Level Average Log Wait Time. For each retailer, we define the "average log national wait time" as the average of the log national wait times for all new products adopted by that retailer. The same definition can be applied at the store level. Specifically, we define:

$$\text{Retailer (Store) Average Log National Wait Time} = \frac{1}{N_i}\sum_{p=1}^{N_i}\log\big(wait_{ip}+1\big),$$

where i indexes retailers (or stores), N_i is the number of new products adopted by retailer (store) i, and $wait_{ip}$ denotes the number of weeks between the product's national release week and the week retailer (store) i first sells product p.

Because our primary interest lies in whether retailers possess external information at the time of adoption, we apply a logarithmic transformation to the national wait time. This transformation compresses the influence of long delays while increasing sensitivity to variation in early adoption. Consequently, the resulting metric is driven primarily by the propensity to adopt products shortly after their national release.

Figure 1 plots each retailer's "share of new products adopted within 3 months of the national release" (blue dots) alongside the "negative average log wait time" (red dashed line). The two series track each other closely, validating the consistency of our measures. The figure also highlights substantial heterogeneity in new product adoption strategies across retailers. Among retailers with the highest adoption propensity, roughly 60% of new items are stocked within three months—a rate approximately

1.5 times that of the slowest adopters.

Figure 1: Relationship Between Retailers' 3 Month New Product Adoption Rate and Wait-Time Measures

Note: Each point represents a retailer. Blue dots indicate the share of the retailer's adopted new products that are introduced within 12 weeks of national release. The red dashed line reports the retailer's negative average log national wait time.

3 Descriptive Evidence

3.1 Retailer Characteristics Linked to New Products Adoption Strategy

We document systematic heterogeneity in retailer characteristics associated with their new product adoption strategies. Specifically, retailers that aggressively introduce new products tend to have broader assortments, more stores, and higher revenue, but also bear a higher rate of product failures. For expositional convenience only, we classify retailers into the following groups:

- **Pioneer retailers:** the 4 retailers with the shortest average log national wait time.
- **Follower retailers:** the 10 retailers with the longest average log national wait time.

Figure 2 visualizes the relationship between adoption speed and key operational metrics. We observe distinct patterns across the following dimensions:

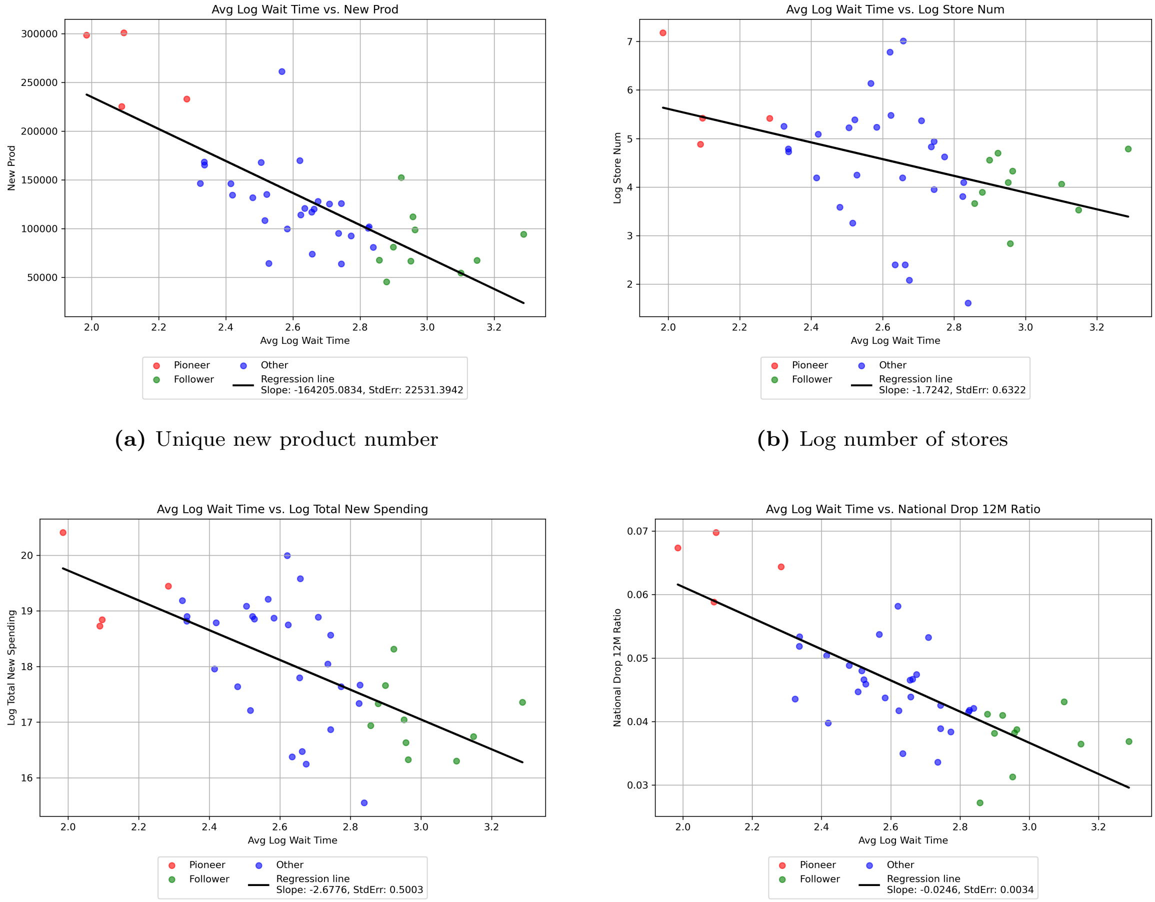
Introduces a larger number of new products: Figure 2a plots each retailer's average log national wait time against the number of unique new products adopted between 2007 and 2019. The relationship is strongly negative: retailers with shorter waits introduce substantially more new products. The four fastest adopters each adopt roughly 250,000 items, whereas the five slowest adopt only about 75,000.

Operate larger store networks with higher revenue: Figures 2b and 2c show how average log national wait time correlates with retailers' log number of stores and log revenue. In both cases, shorter-wait retailers tend to operate larger store networks and generate higher revenue.

Adopt more and higher share of failed products: Figure 2d shows that retailers with shorter waits introduce a higher share of products that fail nationally—defined as products no longer sold anywhere in the United States one year after release. These patterns indicate that faster adopters experiment with a broader set of high-risk products and bear a correspondingly higher failure rate.

To assess whether these patterns are robust across product departments, we regress retailers' average

Figure 2: Retailer Average Log National Wait Time and Store Characteristics, 2007–2019



(a) Unique new product number

(b) Log number of stores

(c) Revenue from new products

(d) Share of products dropped within 12 months

Note: Each point represents a retailer. The x-axis is the retailer's average log national wait time. The y-axis shows, by panel, (a) the number of unique new products adopted, (b) the log number of stores, (c) log revenue from new products, and (d) the share of adopted new products that are dropped nationally within 12 months of release. Statistics are computed over 2007–2019.

log national wait time on four characteristics: the number of new products, the log number of stores, the log revenue from new products, and the share of national failures. Table 1 reports the results separately by department. Across almost all departments, the coefficients are negative and statistically significant: retailers that operate more stores, introduce more new products, generate higher revenue from new products, and carry a higher share of national failures tend to have shorter average log national wait times.

3.2 Store Characteristics Linked to New Products Adoption Strategy

Heterogeneity in new product adoption strategies arises not only at the retailer level but also across the stores they manage. To document the differences between earlier- and later-adopting stores within the same retailer–state store network, we define the following groups:

1. **Pioneer stores:** for each retailer-state group with at least ten stores, the lowest 30% of stores ranked by average log retailer-state wait time.

2. **Follower stores:** for each retailer-state group with at least ten stores, the highest 30% of stores ranked by average log retailer-state wait time.

Table 1: Retailer Average Log National Wait Time and Retailer Characteristics, by Department

Department	Now Prod Num	Log Store Num	Log Revenue	Failure Ratio
All Products	-164205.083***	-1.724***	-2.678***	-0.025***
	(22531.394)	(0.632)	(0.500)	(0.003)
ALCOHOLIC BEVERAGES	-13085.617***	-1.120***	-1.868***	-0.010***
	(1492.235)	(0.364)	(0.306)	(0.001)
DAIRY	-2861.197***	-0.988	-1.952***	-0.015***
	(635.061)	(0.624)	(0.534)	(0.004)
DELI	-1353.302***	-1.502***	-2.249***	-0.044***
	(245.474)	(0.535)	(0.463)	(0.009)
DRY GROCERY	-31733.794***	-1.934**	-2.684***	-0.022***
	(8294.400)	(0.748)	(0.582)	(0.004)
FRESH PRODUCE	-2153.941***	-1.223**	-1.148**	-0.031***
	(549.305)	(0.536)	(0.535)	(0.006)
FROZEN FOODS	-4300.496***	-1.667**	-2.492***	-0.011**
	(980.787)	(0.702)	(0.546)	(0.004)
GENERAL MERCHANDISE	-23081.037***	-0.980**	-2.846***	-0.018***
	(3300.218)	(0.430)	(0.397)	(0.006)
HEALTH & BEAUTY CARE	-23763.878***	-0.862*	-2.031***	-0.007***
	(2783.464)	(0.443)	(0.337)	(0.002)
NON-FOOD GROCERY	-12363.829***	-1.379**	-2.107***	-0.023***
	(2022.250)	(0.599)	(0.500)	(0.004)
PACKAGED MEAT	-585.830**	-0.975*	-0.908*	-0.030***
	(245.611)	(0.537)	(0.485)	(0.004)

Notes: The table reports coefficients from retailer-level OLS regressions ($N = 41$) by RMS department. The dependent variable is the retailer's average log national wait time. Each cell corresponds to a univariate regression on the respective characteristic. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Based on the above grouping definitions, we classify all stores into the corresponding retailer and store types and compute store-level averages for each group. Table 2 reports summary statistics for stores across these categories.

Table 2: Summary Statistics of Store-Level Measures by Retailer and Store Type

	All Store	P Retailer	F Retailer	P-P Store	P-F Store	F-P Store	F-F Store
Total Prod Num Observed	128,160	156,285	94,676	180,786	127,991	102,203	84,224
Annual Prod Num	38,104	45,976	29,739	52,479	38,227	32,278	26,381
Annual New Prod Num	7,265	8,943	5,232	10,427	7,272	5,615	4,679
Annual National New Prod Num	3,296	4,243	2,036	5,178	3,220	2,306	1,692
New Prod PCT	18.57	19.02	17.04	19.48	18.62	16.82	17.24
National New Prod PCT	8.35	9.02	6.52	9.75	8.22	6.84	6.14
National New in New PCT	44.87	47.41	38.27	50.03	44.19	40.62	35.67
Drop Within 3m PCT	18.21	21.56	15.92	22.00	21.44	15.36	16.47
Drop Within 6m PCT	24.45	27.67	22.41	28.04	27.65	21.62	23.19
Drop Within 12m PCT	36.38	38.74	34.03	39.03	38.76	33.14	34.90
Avg National Wait Time	56.81	51.81	67.85	47.19	57.86	63.36	73.24
Avg Log National Wait Time	3.07	2.97	3.28	2.86	3.09	3.17	3.38
Median HH Income 2005-2010	56,225	50,455	54,087	51,934	47,718	54,754	53,190
Median HH Income 2010-2015	58,456	52,503	56,303	53,911	49,641	56,891	55,519
Median HH Income 2015-2020	70,678	62,262	67,237	64,143	58,778	67,740	66,531
Number of Store in the Group	5,940	1,518	588	424	424	159	159
Number of Retailer in the Group	41	4	10	4	4	10	10
Avg Retailer Store Num	145	380	59	106	106	16	16

Variable definitions: Prod Num: The total count of unique products. **New Prod**: Products that are newly introduced to the store. **National New Prod**: Newly adopted products that were nationally released in the same calendar year. **Drop-within-#-month**: The share of new products that forever exit the store within # months of introduction. **Median HH Income**: County-level median household income in the store location.

Group definitions: All Stores includes all stores from the 41 retailers. **P Retailer** and **F Retailer** refer to stores operated by the 4 shortest-wait-time retailers and the 10 longest-wait-time retailers, respectively. **P-P Store** and **P-F Store** refer to pioneer and follower stores within pioneer retailers. **F-P Store** and **F-F Store** refer to pioneer and follower stores within follower retailers.

Stores managed by pioneer retailers differ systematically from those managed by follower retailers:

- **Store scale:** Pioneer retailers operate more stores on average (380 vs. 59).
- **Store size:** Their stores sell a greater number of products (45,976 vs. 29,739).
- **New products:** Their stores introduce more new products, both in levels and shares (8,943

vs. 5,232; 19.02% vs. 17.04%).

- **National new products:** Their stores introduce more nationally released products within a year, again in both levels and shares (4,243 vs. 2,036; 9.02% vs. 6.52%).

- **Failed products:** Their stores drop a higher share of products in a short time after released (21.56% vs. 15.92% in 3-month drop rate).

- **Within network store size difference:** Pioneer retailers show a larger gap in assortment size between their own pioneer and follower stores (52,479 vs. 38,227) compared to follower retailers (32,278 vs. 26,381).

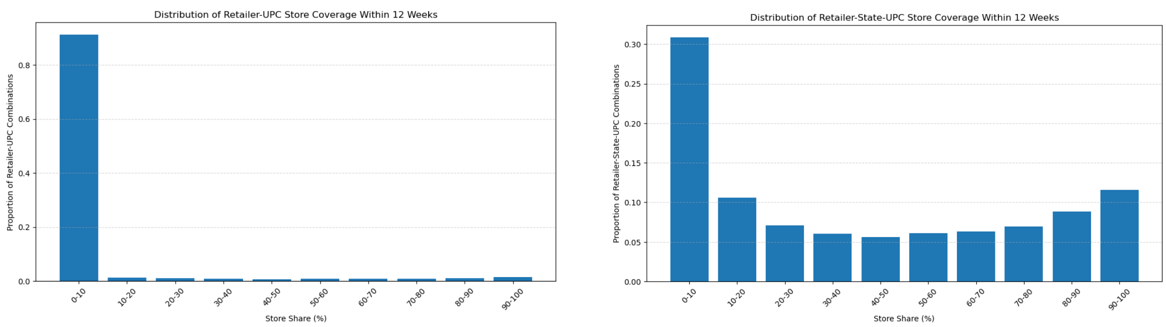
Stores operated by faster-adapting retailers tend to be larger, carry more new products, and discontinue newly introduced products at a faster and higher rate. These store-level disparities suggest that the divergence between retailer with different new product adoption strategies is not merely a mechanical artifact of operational scale, but rather reflects intrinsic differences in their product introduction strategies.

3.3 Non-negligible Share of Products Follow a Staged Roll-out Strategy

It is common for retailers to use a sequential roll-out pattern to adopt new products. When uncertain about a product's potential success, a retailer may first introduce it in a limited number of stores to limit potential losses of failure. The retailer then uses the product's early performance in these test stores to decide whether to discontinue it or to roll it out more broadly across its store network.

At the retailer level, 91% of new products are sold in fewer than 10% of the retailer's stores within the first three months after release (figure 3a). To address the issue of multiple decision makers, we also examine the distribution at the retailer–state level. There are still 31% of new products that are sold in fewer than 10% of stores in the first three months after release (figure 3b). These patterns suggest that testing new products in a small subset of stores is commonly used in retailers' adoption strategies.

Figure 3: Distribution of New Products by the Share of Stores Reached in the First Three Months



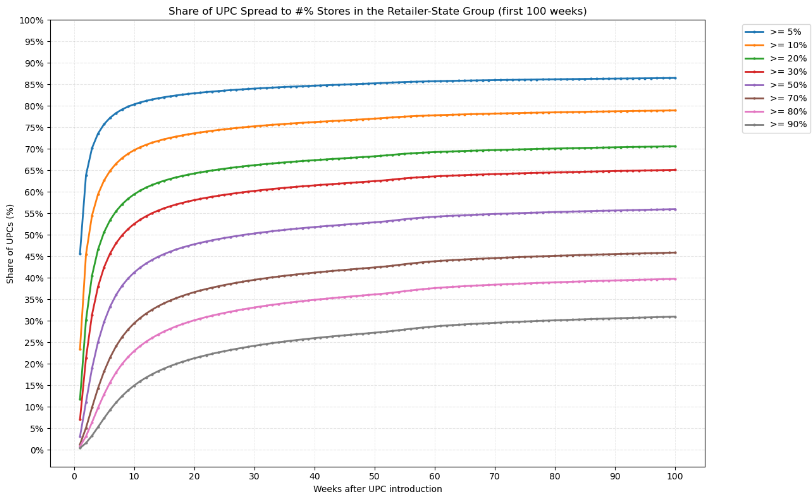
(a) Retailer-level distribution

(b) Retailer–state-level distribution

Note: The figure plots the distribution of new product adoptions by the share of stores reached within the first three months following adoption. Panel (a) is at the retailer level, while Panel (b) is at the retailer–state level.

After being adopted in a subset of stores, product roll-out and distribution are a gradual and ongoing process. Figure 4 illustrates the dynamic expansion of product availability within retailer-state markets. Specifically, it tracks the fraction of products that have penetrated at least $X\%$ of stores over time. By week 10 after introduction, only about 30% of products have been sold in at least 70% of stores; by week 30, this number increases to roughly 40%.

Figure 4: Share of UPCs that Spread to #% Stores in the Retailer-State Group (first 100 weeks)



Note: The figure illustrates the spread of new product adoptions within retailer–state groups. Each curve plots the share of adoptions that have reached a specific store penetration threshold (ranging from 5% to 90%) by the number of weeks since the UPC's first sale in the retailer–state group.

3.4 Heterogeneity in Within-Retailer Spread Dynamics

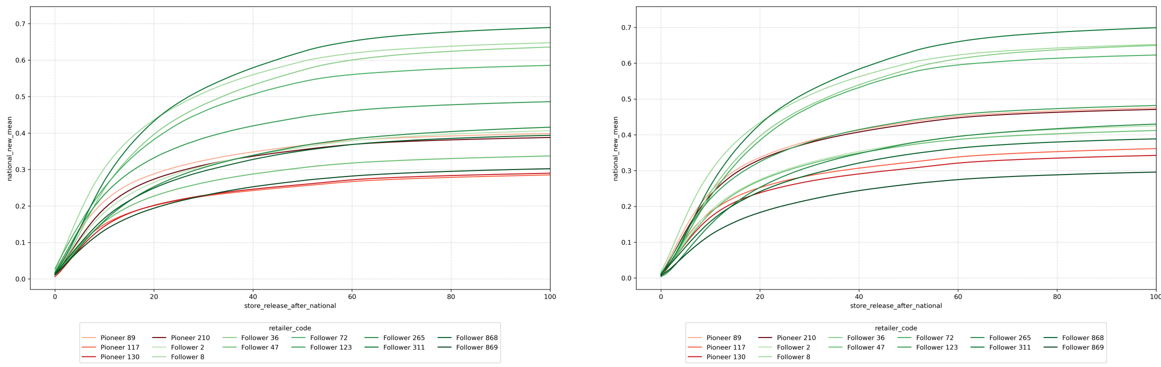
We showed retailers follow a gradual roll-out pattern when introducing new products. This means that it takes time for a product, newly introduced to a retailer chain, for it to spread to the stores within the retailer's chain. Within each retailer, new products are usually adopted in a subset of stores first and then gradually spread to more stores. This process can last for one to two years.

We demonstrate substantial heterogeneity in the extent to which new products reach the stores of the retailer. Figure 5 shows how the share of stores selling a product increases as the national release time grows. The calculation considers the products that the retailer adopted within one year of the national release. We can see that retailers differ in their eventual spread store share. Even when restricting to products adopted by at least three retailers, the standard deviation in average store-reach share across retailers is 0.1507 after 24 month of spread.

All four pioneer retailers actively drop or halt the spread of failing products during the roll-out process, which results in new products reaching only about 30–40% of their stores on average. Conversely, some follower retailers (e.g., 8, 36, 72, 311) rarely drop products during the roll-out, allowing them to reach 60–70% of stores on average. As a result, introducing a product that consumers do not like will sell in larger share of stores, generating greater potential losses.

Among retailers with similar final spread levels, pioneer retailers exhibit faster early spread in the first six months, followed by a flatter trajectory thereafter. This pattern is consistent with the interpretation that pioneers identify successful products earlier and therefore complete their internal spread process sooner.

Figure 5: Average Cumulative Share of Stores Reached Over Time Since National Release



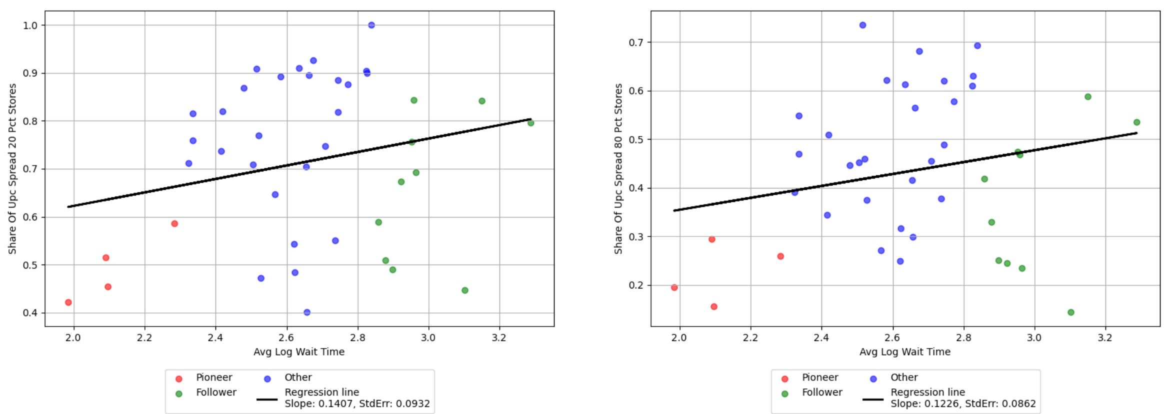
(a) All UPCs

(b) UPCs adopted by at least 3 retailers

Note: The figure plots the average cumulative share of stores reached by new products over the weeks since national release. Panel (a) includes all UPCs (excluding private labels), while Panel (b) is restricted to products adopted by at least three retailers. To make the figure clearer, we include only pioneer retailers and follower retailers.

Different retailers vary in how they roll out products once adopted. Figure 6 plot, for each retailer, the share of all adopted national new products (i.e., products adopted by the retailer within one year of the national release) that eventually appeared in at least 20% and 80% of the retailer's own stores. Among the four pioneer retailers, more than 40% of adopted national new products were sold in only 20% of their stores, and fewer than 30% of products ultimately spread to 80% of stores. In contrast, some other retailers have more than 60% of products that eventually reach over 80% of their stores.

Figure 6: Share of Retailer Adopted National New Products that Spread Across 20% or 80% Stores



(a) Spread to 20% of stores

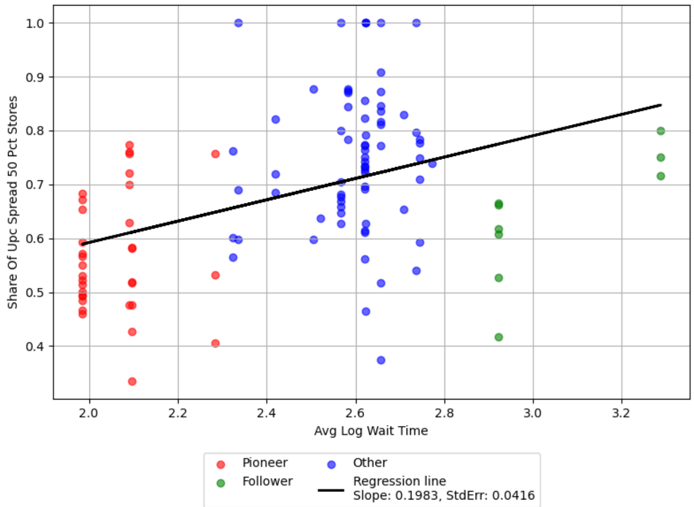
(b) Spread to 80% of stores

Note: Each point represents a retailer. The y-axis displays the share of products adopted within one year of national release that eventually reached at least 20% (Panel a) or 80% (Panel b) of the retailer's stores. The x-axis represents the retailer's average log national wait time.

To control for heterogeneity in network scale and decision-making, we examine retailer–state groups with at least 100 stores. This threshold ensures sufficient scale for analyzing spread while focusing on units likely governed by a single decision maker. Our analysis focuses on national new products adopted by the specific retailer–state group.

Figure 7 confirms that the main pattern holds at this granular level: the early adopting retailers have a larger share of products that fail to reach 50% store coverage.

Figure 7: Share of The Retailer-State Adopted National New Products That Spread to 50% of Stores



Note: Each point represents a retailer–state group with at least 100 stores. The y-axis displays the share of products adopted within one year of national release that eventually reached at least 50% of the stores in the group. The x-axis represents the average log wait time at the retailer level, which is constant across state groups for the same retailer.

4 Potential Mechanism

This section presents suggestive evidence regarding the mechanisms underlying heterogeneous adoption and spread strategies across retailers. We highlight three empirical patterns. First, within a retailer, stronger early sales signals predict subsequent expansion, while weaker signals are associated with discontinuation. Second, larger decision makers expand high-performing products to more stores in absolute terms, consistent with higher returns to experimentation. Third, early national performance predicts adoption by later adopters, suggesting learning from outside signals. Based on these findings, we interpret cross-retailer differences through a scale-based framework and discuss other potential confounded mechanisms.

4.1 Within Retailer, Weak Early Performance is Associated with Discontinuation, While Strong Performance is Linked to Expansion

We next examine the relationship between early sales signals and within-retailer spread. Under an active learning hypothesis, stronger early performance should be associated with wider subsequent distribution, whereas weaker performance should be associated with a higher likelihood of discontinuation. We formalize this relationship using the following specification:

$$Y_{p,r} = \beta \cdot \text{EarlyPerformance}_{p,r} + \alpha_r + \alpha_p + \varepsilon_{p,r},$$

where $Y_{p,r}$ denotes the share of stores in retailer-state group r that sell product p in the 12th month after its first sale in that group. The variable $\text{EarlyPerformance}_{p,r}$ measures the median early performance of product p in the test stores of retailer–state group r, defined as sales relative to the median sales of other products in the same module and store. The term α_r denotes retailer-state fixed effects, and α_p denotes UPC fixed effects. Standard errors are clustered at the retailer-state level.

Target products. The analysis focuses on yogurt at the store–UPC–month level. This category is well-suited for identifying retailer learning due to two factors. First, the category contains many national new products and exhibits substantial heterogeneity across items, making it difficult for retailers to predict which products will succeed. Second, yogurt requires refrigeration and has a short shelf life, causing store-level sales to respond quickly to retailers' spread or drop decisions. Focusing on yogurt therefore allows us to leverage rich store-level variation and estimate more detailed specifications than would be feasible in a pooled cross-category setting.

Early performance measure. We construct the early performance measure in two steps. First, for each store s, module m, and month t, we calculate a benchmark $BaseSales_{smt}$, defined as the median revenue of all UPCs in module m sold in that store-month

$$\text{BaseSale}_{smt} = \text{median}\{\text{Revenue}_{u,s,t} : u \in m\}.$$

We then compute its store-month relative performance as:

$$\text{RelPerf}_{p,s,t} = \frac{\text{Revenue}_{p,s,t}}{\text{BaseSale}_{smt}}.$$

We restrict the sample to stores that begin selling UPC_p within two months of its national release. For these stores, we use $\text{RelPerf}_{p,s,t}$ measured in months $t = 2, 3, 4$ after the national release of UPC_p. Second, for each retailer–state–UPC combination (p, r), we aggregate all valid store-level signals from the constituent stores to define the early performance measure as:

$$\text{EarlyPerformance}_{p,r} = \text{median}\{\text{RelPerf}_{p,s,t}\}_{s,t}.$$

This statistic summarizes how well the new product performs relative to typical products in the same store and module during the early selling period. All early-performance measures are winsorized.

Variables used in the learning regressions. We construct three outcome variables at the retailer–state–UPC level:

- **Store Share**: Share of stores in the retailer–state group that sell the product in the 12th month after the product's first observed sale in that group (baseline).
- **Total Store Share**: Share of stores that ever sell the product at any point after introduction.
- **Share Increase**: Change in store share between months 4 and 12.

Regression results. Across the 14 specifications reported in Tables 3 and 4, the coefficient on the early-performance measure is consistently positive, statistically significant, and stable in magnitude. In every specification, products with stronger early signals are subsequently sold in a larger share of stores within the same retailer–state group. These patterns are consistent with within-retailer learning: retailers expand the distribution of products with favorable early performance and limit the spread of products with weaker initial signals.

Table 3: Relationship Between Early Performance and Subsequent Spread (Models M1–M7)

	M1	M2	M3	M4	M5	M6	M7
Log Median Perf.	0.175***	0.177***	0.268***	0.023*	0.091***	0.171***	
	(0.011)	(0.016)	(0.007)	(0.011)	(0.009)	(0.010)	
Median Perf.							0.244***
							(0.014)
Avg. Unit Price						-1.237***	
						(0.318)	
Y var	store share	store share	store share	share increase	total store share	store share	store share
UPC FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Retailer-State FE	Yes	No	Yes	Yes	Yes	Yes	Yes
SE type	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1
R^2	0.760	0.711	0.268	0.669	0.681	0.763	0.758
N	23532	23532	23532	23532	23532	23532	23532

Notes: Standard errors clustered at the state–retailer level (CRV1). M1 is the baseline specification with 12th-month store share as the dependent variable and both UPC and state–retailer fixed effects. M2 includes only UPC fixed effects. M3 includes only state–retailer fixed effects. M4 uses the change in store share between months 4 and 12 as the dependent variable. M5 uses the total store share as the dependent variable. M6 adds average unit price as a control. M7 replaces Log Median Perf. with Median Perf. as the main regressor.

Table 4: Relationship Between Early Performance and Subsequent Spread (Models M8–M14)

	M8	M9	M10	M11	M12	M13	M14
Log Median Perf.			0.157***	0.139***	0.188***	0.121***	0.150***
			(0.019)	(0.015)	(0.012)	(0.019)	(0.010)
Log P75 Perf.	0.204***						
	(0.011)						
Log Mean Perf.		0.198***					
		(0.011)					
Log Median Perf. × Pioneer						0.087***	
						(0.021)	
Store Share (Month 4)							0.004***
							(0.001)
Y var	store share	store share	store share	store share	store share	store share	store share
UPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Retailer-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE type	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1
R^2	0.763	0.762	0.756	0.747	0.640	0.762	0.778
N	23532	23532	11766	11766	14802	23532	23532

Notes: Standard errors are clustered at the state–retailer level (CRV1). All specifications use the 12th-month store share as the dependent variable and include both UPC and state–retailer fixed effects. M8 replaces Log Median Perf. with Log P75 Perf. as the main regressor. M9 uses Log Mean Perf. as the performance signal. M10 restricts the sample to UPCs in the lower half of the Log Median Perf. distribution. M11 restricts the sample to UPCs in the upper half of the Log Median Perf. distribution. M12 restricts the sample to UPCs that spread to at least three retailers. M13 adds the interaction term Log Median Perf. × Pioneer. M14 adds Store Share (Month 4) as an additional control.

4.2 Within Retailer, larger retailers expand successful products to a greater number of stores

Previous descriptive evidence shows that larger retailers tend to experiment with new products more frequently. A natural question is why this pattern arises. One potential explanation is that testing a new product requires placement in only a small subset of stores, so the direct cost of experimentation does not scale proportionally with retailer size. In contrast, once a product proves successful, larger retailers can spread it across a wider network, generating greater potential gains. Under this logic, the expected return to experimentation may increase with retailer size, helping rationalize why larger retailers appear more willing to test new products.

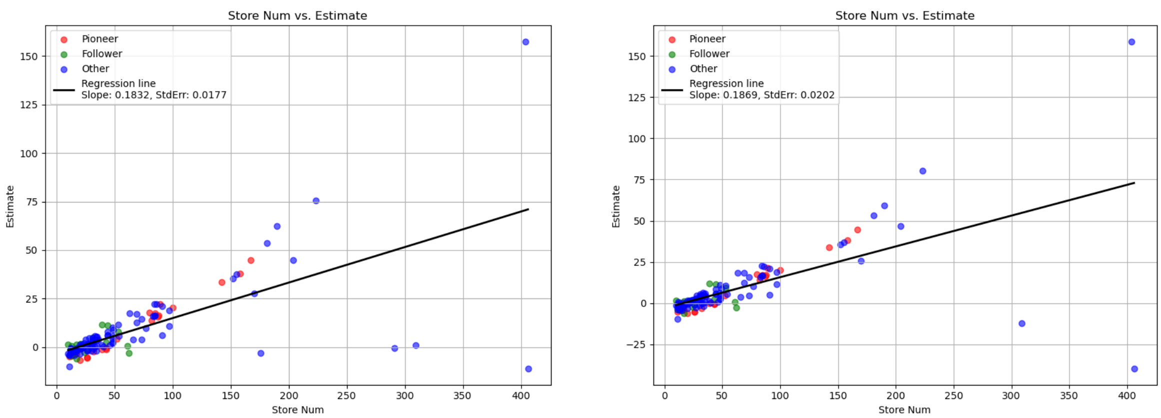
It is mechanically true that larger retailers can spread successful products to more stores because they operate more locations. We therefore look for empirical patterns that are consistent with a mechanism in which larger decision makers expand successful products more aggressively in absolute terms. To avoid conflating multiple decision makers within the same chain, we treat each retailer–state group as a separate retailer (i.e., a separate decision maker). To examine this mechanism, we estimate:

$$Y_{p,r} = \beta_r \cdot \mathbb{1}\{\text{EarlyPerformance}_{p,r} > \tau\} + \alpha_r + \alpha_p + \varepsilon_{p,r},$$

where $Y_{p,r}$ is the number of stores in retailer–state group r that sell product p in the twelfth month after its first sale in that group. The term $\mathbb{1}\{\text{EarlyPerformance}_{p,r} > \tau\}$ equals one when the product's early performance in group r exceeds a threshold τ. In the baseline specification, we set $\tau = 0.5$, which roughly splits products into two equal-sized groups based on early performance. The coefficient β_r captures the incremental number of stores carrying high–early-performance products relative to low–early-performance products within group r. The terms α_r and α_p denote retailer–state and UPC fixed effects.

Figures 8a and 8b plot the estimated β_r against the total number of stores in retailer–state group r. In most cases, groups with more stores exhibit larger values of β_r, meaning that the difference in the number of stores carrying high- versus low–early-performance products is greater in larger groups. This pattern is consistent with the mechanism that larger decision makers obtain greater benefits from spreading successful products and therefore have stronger incentives to experiment.

Figure 8: Extra number of stores reached by high-performance UPCs vs. retailer–state size



(a) All UPCs **(b)** UPCs spread across at least 3 retailers

Note: Each point represents a retailer–state group. The y-axis reports the estimated difference in the number of stores reached by high- versus low-performance products. The x-axis shows the group's total store count. Panel (a) includes all UPCs; Panel (b) is restricted to UPCs adopted by at least three retailers.

4.3 Across Retailers, Products With Good Early Performance Have a Higher Probability of Being Adopted by Later-Adopting Retailers

We define a national new product's *outside early performance* as the ratio of its total sales in the third month after national release to its total sales in the second month. If a product performs well in the first two months, faster-adopting retailers tend to spread it to more stores, leading to higher aggregate sales. Our hypothesis is that waiting retailers can observe this information and incorporate it into their adoption decision. To test this hypothesis, we estimate the following specification:

$$Y_p = \beta \cdot \text{OutsideEarlyPerformance}_p + \gamma \cdot \text{NumTestStores}_p + \alpha_m + \varepsilon_p,$$

where Y_p is the share of waiting retailers that choose to release product p; $\text{OutsideEarlyPerformance}_p$ is the ratio of total sales in the third month after national release to sales in the second month; NumTestStores_p controls for the number of stores that tested the product; and α_m denotes product module fixed effects.

Across a range of specifications, outside early-performance measures consistently predict whether waiting retailers choose to adopt a product. Retailers are more likely to adopt products that exhibit stronger outside early signals, even after controlling for the number of test stores and product-module fixed effects. These patterns support the hypothesis that later-adopting retailers incorporate outside information when making adoption decisions, although we cannot fully rule out the possibility that early national performance partially reflects unobserved product quality.

Table 5: Robustness of Outside Early-Performance Effects on Retailer Adoption Decisions (Full Sample)

	M0	M1	M2	M3	M4	M5
Log Spend Ratio (M3/M2)	0.058***	0.058***	0.096***	0.072***		2.162***
	(0.003)	(0.003)	(0.003)	(0.008)		(0.080)
# Testing Retailers (6M)	0.018***	0.020***		0.020***	0.019***	0.126***
	(0.001)	(0.002)		(0.002)	(0.002)	(0.028)
Log Spend (M3)	0.007***				0.008***	0.431***
	(0.001)				(0.001)	(0.035)
Log Spend Ratio (M4–5 / M2–3)					0.058***	
					(0.003)	
Y var	share	share	share	share	share	number
Products Module FE	Yes	Yes	Yes	No	Yes	Yes
SE type	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1
R2	0.380	0.378	0.207	0.307	0.392	0.192
N	275819	275819	275819	275819	275819	275819

Table 6: Robustness of Outside Early-Performance Effects on Retailer Adoption Decisions (UPCs Adopted at Least in Three Retailers)

	M0_spread	M1_spread	M2_spread	M3_spread	M4_spread	M5_spread
Log Spend Ratio (M3/M2)	0.057***	0.057***	0.085***	0.071***		2.030***
	(0.003)	(0.003)	(0.003)	(0.010)		(0.077)
# Testing Retailers (6M)	0.015***	0.016***		0.016***	0.017***	-0.012
	(0.001)	(0.001)		(0.002)	(0.001)	(0.020)
Log Spend (M3)	0.003**				0.005***	0.318***
	(0.001)				(0.001)	(0.045)
Log Spend Ratio (M4–5 / M2–3)					0.055***	
					(0.003)	
Y var	share	share	share	share	share	number
Products Module FE	Yes	Yes	Yes	No	Yes	Yes
SE type	CRV1	CRV1	CRV1	CRV1	CRV1	CRV1
R2	0.321	0.320	0.194	0.228	0.330	0.149
N	190865	190865	190865	190865	190865	190865

Notes for Tables 5 and 6: Standard errors clustered at the product-module level (CRV1). Models M0–M5 follow the same specification definitions in both tables. M0 includes Log Spend Ratio (M3/M2), # Testing Retailers (6M), and Log Spend (M3), with product-module fixed effects. M1 drops Log Spend (M3) from M0. M2 includes only Log Spend Ratio (M3/M2) with product-module fixed effects. M3 removes product-module fixed effects from M0. M4 replaces Log Spend Ratio (M3/M2) with Log Spend Ratio (M4–5/M2–3). M5 changes the dependent variable to the number of waiting retailers that adopt the product within six months, using the regressors from M0.

4.4 Retailer Strategies: Testing versus Waiting

The descriptive evidence in the previous sections establishes that retailers exhibit substantial heterogeneity in their adopt timing and risk management. Motivated by these patterns, we introduce a conceptual framework that characterizes retailer strategies along a spectrum from *test-oriented* to *wait-oriented* behavior. This framework highlights the trade-off between testing new products early to capture life-cycle profits versus waiting to leverage information generated by others to avoid failures.

Test-oriented retailers. We refer to retailers that actively introduce new products early as *test-oriented retailers*. By experimenting with a broad set of items before their quality is widely known, these retailers aim to identify successful products sooner and capture early revenues. To manage the downside risk of failure, they typically employ a staged roll-out strategy: introducing the product in a limited subset of test stores, observing early signals, and then expanding or discontinuing the item based on performance. Crucially, the incentives for this strategy interact with retailer scale. Because the number of test stores required to generate informative signals does not need to scale one-for-one with total network size, larger retailers can spread the fixed cost of testing over a larger network. Consequently, the expected return from experimentation increases with the number of stores a retailer operates.

Wait-oriented retailers. In contrast, *wait-oriented retailers* choose to delay adoption until uncertainty is partially resolved. By observing signals from other retailers, these retailers can avoid the fixed costs of testing and reduce the probability of carrying failed products. The opportunity cost of experimentation is particularly high for retailers with smaller store networks or tighter shelf-space constraints, as the potential upside from identifying a winner is limited by their small scale. Thus, smaller retailers have weaker incentives to generate their own information and optimally choose to free-ride on the experimentation of larger, test-oriented chains. This strategy relies on the availability and quality of outside information; if cross-retailer signals are noisy or delayed, even wait-oriented retailers may be forced to engage in some degree of testing.

In 5.1, we present a dynamic learning model and conduct a simulation exercise. The simulation shows that even when retailers are identical in all respects except for the number of stores they operate, differences in scale alone can lead them to adopt heterogeneous strategies.

4.5 Other Potential and Confounded Mechanisms

In the preceding discussion, we showed that retailers have different new product adoption strategies. One potential explanation is a scale effect: successful products can eventually be sold in most stores within a retailer's network, while failures are typically dropped early in only a few stores. Larger retailers, therefore, earn higher expected returns from experimentation, and their test costs do not increase proportionally with network size. This makes them more willing to test new products.

Beyond the scale effect, several other mechanisms could also contribute to the observed patterns or be confounded with the heterogeneity in retailers' new product adoption strategies. This subsection briefly discusses these mechanisms.

Shelf space, Store location, and Consumers. Retailers that try more new products tend to operate larger stores. These stores have more shelf space and face lower opportunity costs per tested item. This reduces the effective cost of experimentation and can make large retailers more willing to test new products. Larger retailers also have wider networks and greater variation in store size and location. They often run very large stores in affluent areas and smaller stores elsewhere. Large stores can absorb more new products at lower risk because they have more shelf space and serve higher-income consumers who are more willing to try new items. Larger retailers also serve more diverse customer groups across their different stores. They may be more willing to test products designed for narrower segments, such as items targeted at specific racial or ethnic groups or high-income households.

This can be viewed as a complement to the scale effect discussed above. Once we take into account demographic heterogeneity across a large retailer's stores, the expected payoff from testing new products becomes even higher for large retailers. In our simulations, we consider scenarios in which retailers operate some large stores with lower testing costs.

Lower Risks for Bundle Categories Retailers cannot predict which specific product will succeed, but they may anticipate that certain categories (such as yogurt) will generate some successful items each year. For example, if the market introduces 100 new yogurt products and roughly 10 are expected to succeed, a large retailer that adopts most of the 100 new yogurt is almost guaranteed to carry the eventual winners. Thus, while the risk of each product is high, the category-level risk is much lower. In contrast, a small retailer may only be able to adopt 20 of these items. In that case, it faces a real possibility that none of the 20 products will be successful. The same perceived category-level risk, therefore, looks much smaller for a large retailer than for a small one. However, the expected payoff from testing an individual product remains independent of portfolio size.

Learning ability and operational practices. Retailers also differ in how strongly they react to early performance signals. Some retailers actively adjust roll-out decisions in response to early sales. For these retailers, products with weak early performance tend to remain in a small set of stores or are dropped quickly, while products with strong early performance spread more widely. Other retailers show a weak relationship between early performance and final roll-out. They eventually sell many new products in most stores, regardless of early outcomes. These differences may reflect broader differences in retailers' operational strategies. However, we have not yet found strong and robust evidence of a systematic link between this form of "learning ability," retailer size, and adoption strategies.

Externalities from New Products Testing more new products may create demand-side externalities. A rich and frequently refreshed assortment can attract customers who value variety or who enjoy trying new items. A retailer that experiments more may therefore generate extra traffic and higher sales for the rest of its assortment, which increases the payoff from experimentation. This effect is likely to affect large and small retailers similarly.

Manufacturer relationships and advertising. Large retailers may have stronger bargaining power or closer relationships with manufacturers. Manufacturers may place new products first in their stores, especially in the initial weeks after national release. Large retailers may also have more influence over national advertising strategies and capture greater benefits from advertising spillovers. To assess the role of this channel, we also examine products that retailers adopt within one year of the national release. The differences in adoption strategies across retailers remain, suggesting that this mechanism alone cannot account for the observed heterogeneity.

Based on the above discussion, we suspect that scale effects, together with the greater variety of stores in larger networks, may be the most important explanation for the different new product adoption strategies adopted by large and small retailers. The remaining potential mechanisms are not mutually exclusive with the scale-effect story and are likely to operate simultaneously and to be partly confounded in the data. But each mechanism on its own does not seem sufficient to fully explain the observed differences in strategies.

5 Simulation

5.1 Dynamic Learning Model

Model Setting. Building on the dynamic learning framework (e.g., Erdem and Keane, 1996; Hitsch, 2006; Ching et al., 2013), we develop a parsimonious learning process. Consider a market with a single product i and a single retailer r. In period 0, the product is released nationally with true (but unknown) quality λ. The retailer does not observe λ directly. Instead, the retailer holds a prior belief that λ is normally distributed:

$$\lambda \sim \mathcal{N}(\mu_0, \sigma_0^2),$$

where μ_0 is the prior mean of product quality and σ_0^2 is the prior variance. Given information up to period t, the retailer's belief about λ is normal with mean μ_t and variance σ_t^2.

The retailer owns N stores. In each period t, based on its current belief and the number of active stores, the retailer chooses how many of its stores will sell the product in the next period. This number can be any integer between 0 and N. Information comes from two sources. First, the retailer receives internal signals only from its own stores that actively sell the product in period t. These store-level signals are i.i.d. with mean equal to the true quality. Second, the retailer observes external signals from the broader market regardless of its own adoption decision, albeit with substantial noise.

Similar to Hitsch (2006), when the true product quality is uncertain, retailers may experiment with some products whose one-period expected profit is negative. By doing so, they can learn and identify products that are initially undervalued, and subsequently expand these products to more stores in later periods. For products that truly have low quality, retailers will drop them quickly to avoid long-term losses.

States and actions. The state in period t is

$$s_t = (\mu_t, \sigma_t^2, n_t),$$

where

- μ_t is the mean of the retailer's belief about product quality in period t;
- σ_t^2 is the variance of this belief in period t;
- n_t is the number of stores selling the product in period t.

The action in period t is the choice of how many stores will sell the product in period $t+1$. Let

$$\alpha_t \in \{0, 1, \dots, N\}$$

denote this choice, so that

$$n_{t+1} = \alpha_t. \tag{1}$$

Similar to Erdem and Keane (1996), the state variables do not include sales performance. The decision α_t is made *ex-ante*: the retailer forms an expectation of the information update based on its current belief and the number of upcoming signals, and selects α_t to maximize expected returns given these expectations.

Information and belief updating. In each period t, if $n_t > 0$ the retailer observes the product's sales performance from each of its active stores. We assume that the per-store performance signals are i.i.d. normal:

$$\zeta_{\text{store},j,t} \sim \mathcal{N}(\lambda, \sigma_\varepsilon^2), \qquad j = 1, \ldots, n_t,$$

where σ_ε^2 is the variance of store-level shocks. The inside signal is the average performance across the n_t active stores,

$$\zeta_{\text{inside},t} = \frac{1}{n_t} \sum_{j=1}^{n_t} \zeta_{\text{store},j,t} \sim \mathcal{N}\left(\lambda,\ \frac{\sigma_\varepsilon^2}{n_t}\right) \quad \text{for } n_t > 0.$$

In addition, the retailer receives information from other retailers (outside the chain). Denote this outside signal by

$$\zeta_{\text{outside},t} \sim \mathcal{N}\left(\lambda,\ \sigma_{\text{out}}^2\right),$$

where σ_{out}^2 captures the variability of outside information.

We assume that inside and outside signals are independent. The retailer summarizes all information in period t by a single signal $\zeta_{\text{update},t}$, which is normally distributed around λ with variance $\sigma_{\zeta,t}^2$:

$$\zeta_{\text{update},t} \sim \mathcal{N}\left(\lambda,\ \sigma_{\zeta,t}^2\right),$$

A convenient specification for the variance of the $\zeta_{\text{update},t}$ is

$$\sigma_{\zeta,t}^2 = \left(\frac{n_t}{\sigma_\varepsilon^2} + \frac{1}{\sigma_{\text{out}}^2}\right)^{-1}.$$

Given the prior belief in period t, and the period-t information $\zeta_{\text{update},t}$ with variance $\sigma_{\zeta,t}^2$, the posterior belief in period $t+1$ is normal with mean and variance

$$\sigma_{t+1}^2 = \left(\frac{1}{\sigma_t^2} + \frac{1}{\sigma_{\zeta,t}^2}\right)^{-1} = \left(\frac{1}{\sigma_t^2} + \frac{n_t}{\sigma_\varepsilon^2} + \frac{1}{\sigma_{\text{out}}^2}\right)^{-1} \tag{2}$$

$$\mu_{t+1} = \left(\frac{1}{\sigma_t^2} + \frac{1}{\sigma_{\zeta,t}^2}\right)^{-1} \left(\frac{1}{\sigma_t^2}\,\mu_t + \frac{1}{\sigma_{\zeta,t}^2}\,\zeta_{\text{update},t}\right) \tag{3}$$

When the retailer chooses the action α_t in period t, it already knows the current prior (μ_t, σ_t^2) and expects the update information $E\left[\zeta_{\text{update},t} \mid \mu_t, \sigma_t^2\right] = \mu_t$. Under the learning model in Erdem and Keane (1996), the retailer's expected μ_{t+1} at this stage is normally distributed with $E\left[\mu_{t+1} \mid \mu_t, \sigma_t^2\right] = \mu_t$ and with variance:

$$\text{Var}(\mu_{t+1} \mid \mu_t, \sigma_t^2) = \frac{\sigma_t^4}{\sigma_t^2 + \sigma_{\zeta,t}^2}. \tag{4}$$

Per-period profits. In each period t, the expected per-store profit from selling the product, conditional on belief μ_t, is

$$\mathbb{E}[\pi_{\text{store},t} \mid \mu_t] = f_\pi(\mu_t) - c,$$

where c is a per-store marginal cost and $f_\pi(\cdot)$ is an increasing function of perceived quality. For tractability, we adopt a simple linear specification:

$$f_\pi(\mu_t) = \mu_t,$$

so higher perceived quality raises expected profits one-for-one.

If the retailer increases the number of stores that carry the product between period t and $t+1$, it must pay a one-time, store-level introduction cost. Specifically, when $n_{t+1} > n_t$,

$$C_t = c_{\text{int}}\,(n_{t+1} - n_t)\,\mathbb{I}\{n_{t+1} > n_t\},$$

where $c_{\text{int}} > 0$ is the per-store introduction cost.

If the retailer chooses action α_t in period t, the expected total profit in period t is

$$\pi_t(n_t, \mu_t, \sigma_t^2, \alpha_t) = n_t\big(f_\pi(\mu_t) - c\big) - c_{\text{int}}\,(\alpha_t - n_t)\,\mathbb{I}\{\alpha_t > n_t\}, \tag{5}$$

where $\mathbb{I}\{\cdot\}$ is an indicator function that equals one if its argument is true and zero otherwise. The first term is expected operating profit from the n_t stores that currently carry the product. The second term is the one-time introduction cost incurred when the retailer expands the number of stores selling the product.

Dynamic programming problem. The retailer faces an infinite-horizon dynamic programming problem. In each period t, the state is

$$s_t = (\mu_t, \sigma_t^2, n_t),$$

where (μ_t, σ_t^2) summarizes the belief about product quality and n_t is the number of stores selling the product. Given the current state, the retailer chooses $\alpha_t \in \{0, \ldots, N\}$, which pins down next period's number of stores:

$$n_{t+1} = \alpha_t.$$

Let $\beta \in (0,1)$ denote the discount factor. Beliefs $(\mu_{t+1}, \sigma_{t+1}^2)$ follow the Bayesian updating rules in (3)-(2). The value function satisfies the Bellman equation:

$$V(\mu_t, \sigma_t^2, n_t) = \max\left\{0, \sup_{\alpha_t \in \{0,\ldots,N\}} \mathbb{E}\big[\pi_t(n_t, \mu_t, \sigma_t^2, \alpha_t) + \beta\, V(\mu_{t+1}, \sigma_{t+1}^2, n_{t+1}) \,\big|\, \mu_t, \sigma_t^2, n_t, \alpha_t\big]\right\} \tag{6}$$

To evaluate the expectation term in (6), note that conditional on the current state and action α_t, the n_{t+1}, σ_{t+1}^2, and $\pi_t(\cdot)$ are fixed numbers based on equations (1), (2), and (5). The sole source of uncertainty lies in the posterior mean μ_{t+1}. From the retailer's ex-ante perspective at period t, the μ_{t+1} is normally distributed f_μ with mean μ_t and variance defined in equation (4). Thus, the integral over the value function is taken only with respect to μ_{t+1}:

$$\mathbb{E}\big[V(\mu_{t+1}, \sigma_{t+1}^2, n_{t+1}) \mid \mu_t, \sigma_t^2, n_t, \alpha_t\big] = \int_{-\infty}^{\infty} V(\mu', \sigma_{t+1}^2, n_{t+1})\, f_\mu(\mu' \mid \mu_t, \sigma_t^2, n_t)\, d\mu'.$$

Another assumption is that the retailer can permanently drop the product once it is deemed unprofitable. The term $\max\{0, \cdot\}$ captures the option to stop selling the product and avoid future losses.

We solve the retailer's dynamic programming problem using value function iteration. The state space is discretized over a three-dimensional grid for (μ_t, σ_t^2, n_t), where μ_t lies on a 101-point grid, σ_t^2 on a 500-point grid, and n_t on $0, \ldots, N$. This discretization provides an approximation of the value function over the relevant belief and roll-out states. The resulting optimal policy rule is then used in the simulation exercises reported below.

5.2 Simulation Results

Setup. To illustrate the model mechanisms, we simulate retailers' dynamic adoption decisions in a stylized environment. We assume there is no retailer-level introduction cost and only store-level introduction costs. Consequently, the advantage of scale arises solely from the option to expand successful products across a larger network. In each simulation, a market introduces 100 products with heterogeneous qualities. Retailers start with mean-zero normal priors and update beliefs using the Bayesian learning rules described in Section 5.1. We report results based on 200 independent market simulations.

We compare a large retailer ($N = 30$) and a small retailer ($N = 10$) across five environments. These environments vary by information source, signal precision, and testing costs:

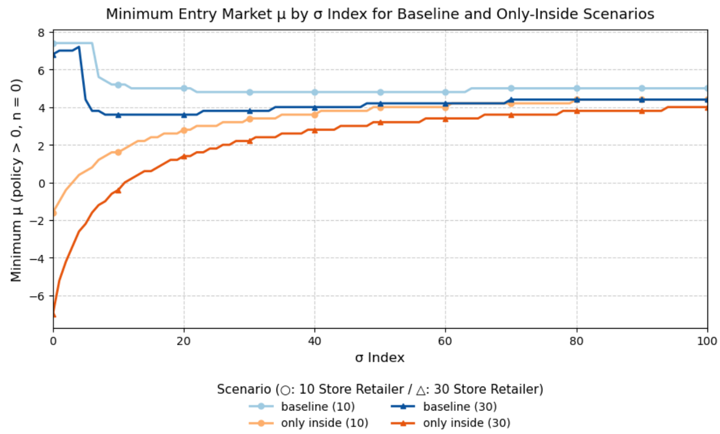
1. **Model 1 (Internal Learning Only)** Retailers learn exclusively from their own store signals.
2. **Model 2 (Internal + Outside Learning)** Retailers observe external market signals in addition to internal ones. This serves as the baseline for evaluating asymmetric advantages. Models 3, 4, and 5 use this specification as the benchmark.
3. **Model 3 (Learning Ability Advantage)** Large retailers receive higher precision internal signals (lower noise), while small retailers maintain baseline precision.
4. **Model 4 (Cost Advantage)** Large retailers incur a lower introduction cost for the initial testing store.
5. **Model 5 (Combined Advantage)** Large retailers possess both the higher signal precision of Model 3 and the lower testing costs of Model 4.

Minimum expected quality thresholds with and without outside information. For each model, we plot the minimum expected quality threshold required to initiate product testing, as derived from the retailer's optimal policy. Without outside information (figure 9a), both retailer types adopt aggressive testing strategies. Since waiting yields no new information, retailers must proactively test new products in order to identify successful ones.

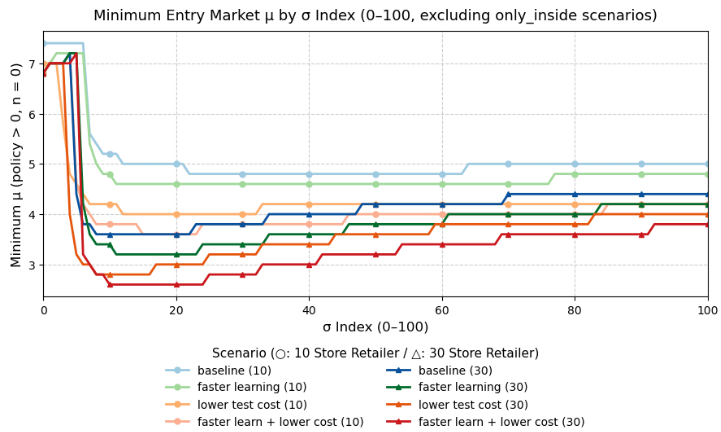
In the presence of outside information (Figure 9b), retailers exhibit increased caution. The availability of external signals creates an information externality, increasing the option value of waiting and encouraging free-riding. Nevertheless, large retailers consistently maintain lower thresholds than their smaller counterparts. The higher continuation value derived from deploying successful products across a larger network incentivizes earlier experimentation, offsetting the free-riding motive.

Figure 9: Minimum Entry Market μ by σ Index Across Learning Environments

(a) Baseline vs. Internal Learning Only



(b) Outside Learning Scenarios

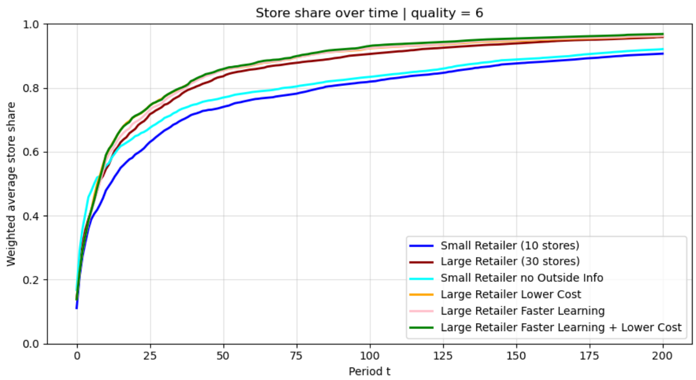


Note: The figure plots the minimum expected quality threshold (μ) required to initiate testing. The x-axis is the index of the discrete uncertainty grid (σ). It can be interpreted as the equivalent number of single-store-level signals observed. Panel (a) compares Internal Learning Only (Model 1) with Baseline (Model 2) for large ($N = 30$) and small ($N = 10$) retailers. Panel (b) compares Baseline (Model 2, $N = 30$) with Learning Advantage (Model 3), Cost Advantage (Model 4), and Combined Advantage (Model 5).

Learning ability, test costs, and willingness to experiment. In figure 9b, we also examine the impact of faster learning and testing costs. We model "faster learning" as a reduction in the standard deviation of store-level signals (e.g., from 20 to 14.14) and "cost advantage" as a reduced introduction cost for the initial test store (e.g., from 40 to 20). In Models 3–5, large retailers receive these advantages relative to the baseline. The simulations demonstrate that larger network scale, higher learning ability, and reduced entry costs independently increase the propensity to experiment: in each dimension, the minimum expected quality threshold shifts downward. Moreover, these forces are complementary. A large retailer combining high-precision learning with low entry costs exhibits a substantially more aggressive experimentation strategy than a baseline small retailer.

Learning and diffusion of a profitable product. We then analyze the dynamic diffusion of a single product whose quality is above or below the profitability threshold. Figure 10 plots the network penetration (share of active stores) specifically for the profitable product. Under complete information, adoption would be immediate and universal. Under uncertainty, large retailers initiate sales earlier and achieve higher penetration than small retailers. This diffusion is further accelerated in Models 3–5 by faster learning and lower testing costs. The figure also underscores how outside information can induce conservative behavior.

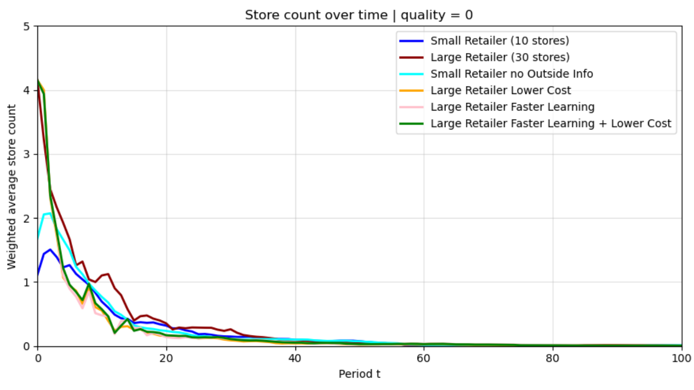
Figure 10: Average Share of Store Selling the Profitable Product Over Time



Note: The figure plots the average share of stores selling a profitable product across simulation markets over time. The curves compare diffusion paths for large ($N = 30$) and small ($N = 10$) retailers across different learning models.

Diffusion and dropping of failed products. For failed products (quality below the zero-profit threshold), large retailers' aggressive testing strategies result in higher initial exposure. In the early stages (e.g., the first 10 periods), the count of stores carrying failed products is higher among large retailers than small retailers. However, due to superior information aggregation (via larger networks or faster learning), large retailers identify low-quality products more quickly and discontinue them sooner. Consequently, the penetration of failed products declines more rapidly for large retailers. These simulation results mirror the empirical patterns: large retailers experiment more broadly and expand successful products, yet—despite higher initial exposure to failures—are better positioned to correct mistakes through efficient learning and decisive exit.

Figure 11: Average Share of Store Selling the Failed Product Over Time



Note: The figure plots the average count of stores selling a failed product across simulation markets over time. The curves compare diffusion paths for large ($N = 30$) and small ($N = 10$) retailers across different learning models.

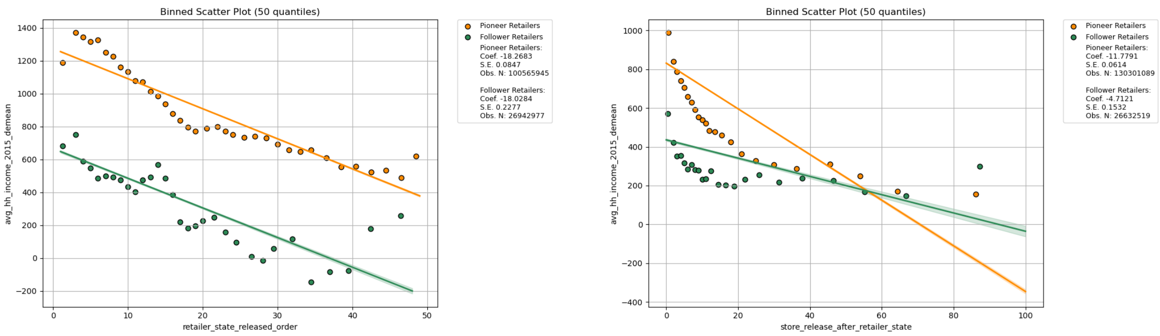
6 Implications

6.1 Inequality

The preceding analyses show that retailers rarely introduce risky national new products to all stores at once. Instead, they typically pilot products in a small subset of stores and then expand or discontinue them over the following one to two years. This roll-out process raises a natural question: does the information used to guide spread and drop decisions systematically over-represent the preferences of certain consumer groups?

Consistent with this concern, we find that early tests are disproportionately conducted in larger stores located in higher-income counties. As a result, the early performance signals that inform subsequent roll-out decisions may be tilted toward the shopping patterns of more affluent consumers. This tilt generates a distinctive within–retailer-state diffusion path: for a given new UPC, distribution often begins in higher-income locations and reaches lower-income locations later. Figure 12a shows that the earliest stores to adopt a UPC are located in counties with significantly higher median incomes, a premium that dissipates as the product spreads to later-adopting stores. Figure 12b confirms that this gradient remains robust when measuring diffusion by the time elapsed since the retailer's initial launch, mitigating concerns that short-run logistical or operational shocks drive the ordering; the pattern remains similar.

Figure 12: County Level Household Demeaned Income in Store Location and Store-UPC Adopt Timing



(a) UPC Adopt Order within Retailer-State Group

(b) Store Wait Time after Retailer-State Released

Note: The left panel shows the relationship between adopt order and local income. The x-axis indexes the release order (the k-th store in the retailer-state to adopt the UPC), and the y-axis reports the retailer-state–demeaned county household median income of the adopting stores. The right panel replicates this analysis using retailer-state wait-time bins (defined as the number of weeks elapsed between the retailer-state group's initial launch and the individual store's introduction) on the x-axis to address potential short-run logistical or operational shocks.

Because early tests are skewed toward higher-income stores, the performance signals determining a product's fate may place disproportionate weight on affluent preferences. Consequently, lower-income consumers may face an informational exclusion: by the time innovations reach their local stores, the assortment has often already been filtered by signals generated in richer neighborhoods. This mechanism has two implications. First, on the consumer side, it can create an access gap: lower-income households experience delayed access to successful innovations and may never see products that would have served their needs but failed to gain traction in high-income test markets. Second, on the firm side, it may increase the risk of Type II errors (false negatives): optimizing for signals dominated by affluent shoppers can lead retailers and manufacturers to discontinue products that perform weakly in test markets but would have been profitable in specific segments, potentially discouraging investment in products targeted to the broader population.

More broadly, the descriptive evidence and the model highlight how information generated in early-testing stores and by test-oriented retailers can propagate through the system. Information flows not only from early-testing stores to the rest of the network, but also from more test-oriented retailers to more wait-oriented retailers. Understanding this information flow is important for evaluating industry practices and voluntary guidelines aimed at improving access to appropriate new products across income groups while preserving the risk-management benefits of test-then-spread strategies. For example, retailers could allocate some testing capacity to stores spanning the income distribution, or adopt more targeted experimentation in lower-income areas, to reduce informational imbalance without abandoning staged roll-outs.

6.2 Retailer Concentration and Competitive Asymmetry

Beyond consumer-side inequality, our findings may also have implications for competitive dynamics across retailers. The central mechanism emphasized in this paper—that the expected returns to experimentation scale with the size of a retailer's store network—can confer an advantage on larger chains. The direct costs of piloting a product (e.g., allocating shelf space, operational adjustments, and the risk of early losses) need not rise proportionally with network size, while the upside from identifying a "winner" can be realized over a larger number of stores. As a result, larger retailers may find it privately optimal to test earlier and on a broader set of items, potentially allowing them to bring successful innovations to their customers sooner.

If consumers value variety and the timely availability of new products, earlier access to successful innovations could strengthen a retailer's perceived assortment quality and, in turn, affect demand allocation across retailers. In this setting, smaller retailers—facing weaker private incentives to generate information through independent testing—may rationally rely more on learning from the outcomes generated by test-oriented retailers and adopt a "wait-and-see" approach. While such behavior can reduce exposure to failures, it may also delay access to high-performing products and limit differentiation. Over time, these forces could contribute to persistent performance gaps and potentially reinforce concentration trends, although the magnitude and relevance of this channel are ultimately empirical questions and may depend on other factors such as consumer switching costs, manufacturer contracting, and local market structure.

7 Conclusion

This paper studies how grocery retailers manage the risks associated with nationally released new products and how these risk-management strategies shape diffusion across stores and consumer segments. Using Nielsen RMS data from 2006–2019 matched to county-level income from the ACS, we document three empirical patterns. First, retailers differ systematically in how quickly they adopt national new products and in how aggressively they subsequently spread or discontinue them within their store networks. Second, within retailers, early performance in a subset of test stores strongly predicts subsequent expansion and dropping, consistent with active learning from early sales signals. Third, retailer scale and geography jointly shape experimentation: larger retailers test more products and spread successful items more widely, and their early signals are disproportionately generated in larger stores located in higher-income areas.

We interpret these patterns through a dynamic learning framework in which retailers choose how many stores to expose to a new product while updating beliefs about its quality using both inside and outside information. The model illustrates how differences in scale—and in the availability of outside signals—can produce heterogeneous "test-versus-wait" strategies even when products are ex ante identical. Taken together, the evidence and the model suggest that information produced by early-testing stores and test-oriented retailers does more than mitigate new-product risk: it can also shape whose preferences are most reflected in which innovations survive and spread, thereby affecting the distribution of timely access to new products across neighborhoods. Characterizing this information flow is therefore useful for assessing industry practices and potential policies aimed at improving access to appropriate innovations across income groups while preserving the efficiency benefits of staged roll-outs.

Several limitations point to promising directions for future work. First, the analysis abstracts from potential demand-side externalities of assortment. Consumers may value variety, and the availability of preferred brands (Briesch et al., 2009), and assortment breadth itself may affect choice (Kwak et al., 2015), implying that experimentation could generate spillovers beyond the focal product. Second, we do not model time-varying store ownership over the sample period. Because we link stores to retailers using a single ownership snapshot (e.g., 2019), mergers, acquisitions, and divestitures may lead to measurement error in store-retailer networks. Finally, we observe that later-introduced products tend to have higher unit prices than earlier-introduced products within the same module, consistent with the possibility that later arrivals are positioned toward more affluent consumers or more competitive segments (Jaravel, 2019). Incorporating these channels—together with retailer–manufacturer contracting and endogenous pricing—would help clarify how the private incentives to test and spread new products map into consumer welfare and the distributional impacts emphasized in this paper.

References

[1] Amano, T., and Tamayo, J. (2025). New product diffusion within retailers: The effect of managerial quality on rollout. *Harvard Business School Working Paper*, No. 25-041.

[2] Aparicio, D., and Simester, D. (2022). Price frictions and the success of new products. *Marketing Science*, 41(6), 1057–1073.

[3] Becerril-Arreola, R., Bucklin, R. E., and Thomadsen, R. (2021). Effects of income distribution changes on assortment size in the mainstream grocery channel. *Management Science*, 67(9), 5878–5900.

[4] Briesch, R. A., Chintagunta, P. K., and Fox, E. J. (2009). How does assortment affect grocery store choice? *Journal of Marketing Research*, 46(2), 176–189.

[5] Bronnenberg, B. J., and Mela, C. F. (2004). Market roll-out and retailer adoption for new brands. *Marketing Science*, 23(4), 500–518.

[6] Cheung, W. C., Simchi-Levi, D., and Wang, H. (2017). Dynamic pricing and demand learning with limited price experimentation. *Operations Research*, 65(6), 1722–1731.

[7] Ching, A. T., Erdem, T., and Keane, M. P. (2013). Learning models: An assessment of progress, challenges, and new developments. *Marketing Science*, 32(6), 913–938.

[8] Erdem, T., and Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, 15(1), 1–20.

[9] Ferreira, K. J., and Mower, E. (2023). Demand learning and pricing for varying assortments. *Manufacturing & Service Operations Management*, 25(4), 1227–1244.

[10] Garber, T., Goldenberg, J., Libai, B., and Muller, E. (2004). From density to destiny: Using spatial dimension of sales data for early prediction of new product success. *Marketing Science*, 23(3), 419–428.

[11] Gielens, K., and Steenkamp, J.-B. E. M. (2007). Drivers of consumer acceptance of new packaged goods: An investigation across products and countries. *International Journal of Research in Marketing*, 24(2), 97–111.

[12] Handbury, J., and Weinstein, D. E. (2015). Goods prices and availability in cities. *The Review of Economic Studies*, 82(1), 258–296.

[13] Hitsch, G. J. (2006). An empirical model of optimal dynamic product launch and exit under demand uncertainty. *Marketing Science*, 25(1), 25–50.

[14] Jaravel, X. (2019). The unequal gains from product innovations: Evidence from the U.S. retail sector. *The Quarterly Journal of Economics*, 134(2), 715–783.

[15] Kwak, K., Duvvuri, S. D., and Russell, G. J. (2015). An analysis of assortment choice in grocery retailing. *Journal of Retailing*, 91(1), 19–33.

[16] Victory, K., Nenycz-Thiel, M., Dawes, J., et al. (2021). How common is new product failure and when does it vary? *Marketing Letters*, 32(1), 17–32.