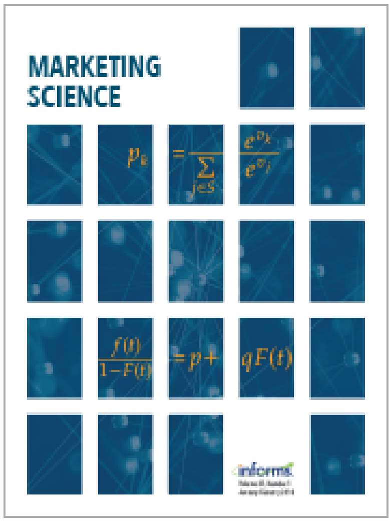


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Price Frictions and the Success of New Products

Diego Aparicio, Duncan Simester

MARKETING SCIENCE
Vol. 41, No. 6, November–December 2022, pp. 1057–1073
ISSN 0732-2399 (print), ISSN 1526-548X (online)
https://pubsonline.informs.org/journal/mksc

Price Frictions and the Success of New Products

Diego Aparicio,[a] Duncan Simester[b,*]

[a] IESE Business School, University of Navarra, Barcelona 08034, Spain; [b] Sloan School of Management, Massachusetts Institute of Technology, Cambridge, Massachusetts 02142
*Corresponding author
Contact: daparicio@iese.edu, https://orcid.org/0000-0003-4964-6745 (DA); simester@mit.edu, https://orcid.org/0000-0003-2758-0116 (DS)

Received: June 8, 2020
Revised: August 2, 2021; December 14, 2021
Accepted: January 2, 2022
Published Online in Articles in Advance: July 26, 2022

https://doi.org/10.1287/mksc.2022.1367

Abstract. The literature has documented that price frictions limit the frequency of price changes. We show that they are also associated with the failure of new products. Using the IRI academic data set, we identify new products that have low initial sales. When price frictions are high, retailers are less likely to adjust the price, and instead are more likely to discontinue the new product. We replicate the results by investigating retailer price and product line adjustments following the opening of a new store. We investigate three settings in which retailers may be reluctant to adjust prices on a new product: (a) when there are no price changes on related products, (b) when state-level pricing laws require price stickers on each package, and (c) when the initial prices end in 99¢. The sources of variation are very different across these settings, ranging from the timing of wholesale price changes to variation in state consumer protection laws to kinks in the demand curve associated with 99¢ price endings. Despite this diversity, our findings are consistent, suggesting that larger price frictions coincide with a higher probability that new items are discontinued when initial sales are low. This consistency leads us to conclude that it is more plausible that the effect is causal, rather than an artifact of endogeneity.

History: Avi Goldfarb served as the senior editor for this article and Christophe Van den Bulte served as the associate editor for this article.
Supplemental Material: The data and online appendix are available at https://doi.org/10.1287/mksc.2022.1367.

Keywords: price frictions • pricing • new products • new stores

1. Introduction

There is an extensive literature studying how retailers' decisions to change prices are affected by "price frictions." These frictions range from capacity constraints that limit how many pricing decisions managers can make to in-store labor costs incurred when changing shelf labels. Although this literature has focused on the relationship between price frictions and the frequency of price changes, we show that pricing frictions are also associated with new product failure. When price frictions are high, retailers are less likely to respond to low initial sales of a new product by adjusting the price, and instead are more likely to discontinue the product.

We use the IRI academic data set and focus on three types of variation. The first type of variation focuses on the timing of price changes on related products, where throughout this paper we define related products as products in the same brand, category, and store. Studies describing the processes that retailers use to set prices document that retail price changes are often scheduled in advance. We show that price changes are also coordinated across items. For example, all of the varieties of Colgate toothpaste tend to change price at similar times each year across all of the stores in the same retail chain. Moreover, the timing of price changes on related items is associated with changes in how retailers act when initial sales of a new product are low. If there are price changes on related items, then there is a higher probability that retailers will adjust the price of the new product. In contrast, if no related items have a price change, then there is an increased probability that the retailer will discontinue the product.

Item pricing laws contribute a second type of variation. These laws require that retailers place price stickers on every unit of each item, and a price change requires a change of all of these stickers. This introduces a friction that hinders price changes, but which arises only in states with item pricing requirements. We show that in those states, retailers are less likely to respond to low initial sales on a new item by changing prices, and instead are more likely to discontinue the item (compared with states that do not have item pricing requirements).

The third source of variation focuses on price endings. Consumer packaged good retailers often charge prices that end in 99¢ (e.g., $1.99 or $2.99). This is generally attributed to belief among retailers that there is a kink in the demand curve around these price endings, so that demand is more sensitive to a price increase than a price decrease. There is considerable evidence in the literature documenting both the prevalence of 99¢ price endings and the reluctance of retailers to change prices when the current price has a 99¢ ending. We show that if the original price of a new product ends in 99¢, and initial sales are low, retailers are again more likely to discontinue the product instead of adjusting the price (compared with when the price does not end in 99¢).

We replicate our findings by repeating the analyses using new store openings. Just like new products, retailers can respond to low initial sales of an item in a new store by adjusting the price or discontinuing the item. We use the same three types of variation and obtain the same pattern of findings. When price frictions are high, retailers are less likely to respond to low initial sales in a new store by adjusting the price. Instead, they are more likely to discontinue the item (compared with when price frictions are low).

The variation in item pricing laws between states is arguably an exogenous source of variation in price frictions. However, the timing of scheduled price changes and the use of 99¢ price endings are clearly endogenous. For this reason, when presenting each set of findings, we are careful to report the findings as associations and to avoid claiming that the relationships are causal. However, in our conclusions, where we discuss and interpret the findings, we highlight that the three types of variation have notably distinct sources. We will argue that it is more plausible that there is a causal relationship between price frictions and retailers discontinuing items with low initial sales, compared with the alternative argument that all three relationships are artifacts of different types of endogeneity.

1.1. Literature Review

Our work relates to several literatures in marketing and economics. We discuss each of these and our contributions to them.

The research on price frictions is extensive. It distinguishes between the frequency of price changes and obstacles to price changes. A focus of the literature is establishing that these obstacles cause less frequent price changes. Any potential obstacle to a price change is labeled as a price friction, and the range of price frictions that have been studied is extensive. Some price frictions arise because of internal organizational constraints, such as managerial capacity or in-store labor capacity. Other potential sources of price frictions include customer reactions to price changes or mere inertia.

We start by reviewing the work that has documented the internal organizational processes associated with changing prices. For example, Zbaracki et al. (2004) study pricing practices at a large industrial firm using a combination of ethnographic and quantitative data. They conclude that the managerial costs of price adjustments are substantial, and include "the cost of information gathering and analysis, systems cost, and the cost of the managerial time spent on the evaluation and decision of price changes" Zbaracki et al. (2004, p. 515). Levy et al. (1998) conduct a similar study focusing on the price change process at five large supermarkets and one large drugstore chain. They document that the price change process is complex and includes eight steps, involving both managerial resources and in-store labor resources. Managers are engaged before the price change to plan the change, and then after the price change to correct errors. The in-store labor is used to print new shelf labels, find the items on the shelves, and then change the price labels.

Anderson et al. (2015) describe the internal policies of a large national retailer that limits price changes to 100 items per week. This policy is designed to ensure that there is sufficient labor available in the retailer's stores to implement the price changes. Although prices on these 100 items may not change in every store, the policy explicitly restricts the centralized pricing team from changing prices on other items (in that week). The policy is enforced by counting the number of items that have price changes each week, and if the 100-item ceiling is exceeded, the bonuses paid to the pricing team are reduced.

There are several studies that directly measure the cost of price adjustments in retail markets. Levy et al. (1997) provide measures of price adjustment costs at five large supermarket chains. They report that changing prices in a large supermarket chain is a complex process that requires considerable resources to produce new shelf labels, find the items on the shelves, replace the price labels, and supervise the entire process. Dutta et al. (1999) also measures the in-store labor costs of producing new price tags and changing the price tags on store shelves, and confirm that the supermarket findings in Levy et al. (1997) generalize to drugstores. Related findings are reported by Levy et al. (1998), Slade (1998), and Cecchetti (1986).

Instead of measuring the cost of changing prices, several previous studies have used the approach that we use in this paper, measuring how retailers respond to these costs. For example, Levy et al. (2010) argue that the cost of price changes is higher during the Thanksgiving-to-Christmas holiday period, because in-store employees are engaged in other activities because of higher store traffic. They show that prices are less likely to change during holiday periods. Anderson et al. (2015) recognize that retailers often charge the same price for different flavors and colors of the same item. For example, all of the colors of a nail polish brand share the same price, and so when the price of this brand of nail polish changes, the price must be changed on every color variant. They predict that on items with more variants, retailers will be less likely to change the retail price when the wholesale price changes. Their findings offer strong support for this prediction.

Collectively, these studies confirm that when changing prices, retailers incur a meaningful cost in both managerial resources and in-store labor. There is now considerable evidence that these costs contribute to less frequent price adjustments. We will show that when these costs are high, retailers are also more likely to discontinue new products that have low initial sales. The impact of price frictions extends beyond just price changes, to also affect product assortment decisions.

We focus on two events in which retailers face initial demand uncertainty: new stores and new products. We chose these events as we expect that demand uncertainty increases the likelihood that retailers will make adjustments after observing initial sales. Doraszelski et al. (2018) and Huang et al. (2022) also investigate how firms learn about demand after entering a new market. Doraszelski et al. (2018) focus on the United Kingdom's deregulation of the electricity generation system and report that in the early phase of the newly deregulated market, firms changed bids more frequently and by larger amounts, compared with subsequent phases. Huang et al. (2022) study the privatization of the Washington State liquor market, which led existing grocery chains to enter the liquor market for the first time. In the initial periods, price changes were large and heterogeneous, whereas in subsequent periods, prices converged to more stable levels.

Several other papers have studied how firms respond to demand uncertainty. Early work by Pashigian (1988) and Pashigian and Bowen (1991) shows that fashion retailers' markdowns can be explained by uncertainty about demand for different styles. Caro and Gallien (2007) study the extent to which fast-fashion retailers can optimize prices and assortments throughout the season. Hitsch (2006) studies how demand uncertainty affects product entry and exit in the cereal industry.

Our findings are also related to papers that use cost shocks to understand pass-through of wholesale price changes. McShane at al. (2016) characterize pricing decisions as a two-stage process, in which managers first decide whether to change prices, and then decide upon the size of the adjustments. Ray et al. (2006) argue that if it is unprofitable for retailers to make small retail price adjustments, this can make it more profitable for manufacturers to engage in small wholesale price increases. Ailawadi and Harlam (2009) study pass-through of manufacturer trade promotions to retailers' temporary price discounts. They report heterogeneous estimates of pass-through; some products have zero pass-through, and other products have over 100% pass-through. Nijs et al. (2010) use detailed manufacturer cost data and find variation in pass-through across each of the manufacturer's vertical channels. Nakamura and Zerom (2010) study timing and pass-through using wholesale prices in the coffee industry. Meza and Sudhir (2010) describe heterogeneous price adjustments to cost shocks for low- and high-selling items in periods of high and low demand. As we discuss in Section 3, the pass-through of wholesale price changes can contribute to the scheduling and coordination of retail price changes. Because wholesale price changes are passed through to retail prices, one source of variation in the timing of scheduled price changes is variation in the timing of wholesale price changes.

There is a separate literature that studies retail product assortments and pricing strategies. Hwang et al. (2010) describe assortment similarities between supermarket stores using Nielsen scanner data. The authors document how these similarities depend on factors such as chain ownership, clientele, and store competition. The authors report significant assortment variation across chains in the same market, as well as within chains across states, which suggests that retailers tailor assortments to market conditions. DellaVigna and Gentzkow (2019) and Hitsch et al. (2021) find that retail chains tend to have specialized assortments and prices. Hwang and Thomadsen (2015) use the IRI data to document large dispersion in market shares of leading brands across retail stores, even for stores located in the same market. Ellickson and Misra (2008) and Aparicio et al. (2021) study supermarket pricing across stores in the same market and find substantial local heterogeneity in prices across stores, including stores in the same chain and stores in competing chains. Our work highlights that adjustments in retail assortments following the introduction of a new product and following the opening of a new store both appear to be associated with variation in price frictions.

1.2. Organization of this Paper

This paper continues in Section 2 with a discussion of the data and definition of measures. We focus on new product introductions and the timing of price changes on related products in Section 3. In Section 4, we consider item pricing requirements and retailers' preferences for 99¢ price endings. In Section 5, we replicate the new product findings using new store openings. The paper concludes in Section 6 with a summary of the findings, proposals for future research, and a discussion of endogeneity and causation.

2. Description of the Data

We use the IRI academic data set, which includes prices and sales for U.S. grocery and drugstore retailers between 2001 and 2006. The data cover over 30 product categories (e.g., beer, coffee, milk, shampoo) and 47 major metropolitan areas (e.g., Chicago, Los Angeles, Boston). Transaction data are available at the store-week-UPC level (UPC stands for Universal Product Code) level. The identities of the chains are masked, but each store can be paired with a retail chain code. We will use the terms "item" and "product" interchangeably to refer to a unique UPC. The UPCs can be matched across retailers and across time. Bronnenberg et al. (2008) provide a complete description of the data set.

The IRI data set contains store details, including the city, the estimated annual sales, and the opening and closing weeks (from the lens of IRI's data collection). We restrict attention to grocery retailers, because the vast majority of the data represent grocery retailers rather than drugstore retailers. The data set assigns a brand to each UPC, and we use this brand information to identify related items that share the same brand, category, and store. The brand definitions are relatively precise, so that Coca-Cola, Diet Coke, RC, Diet RC, and Mr. Pibb are all treated as separate brands.[1]

We summarize key characteristics of the data in Table 1. The transaction data include six years of transactions extending from January 2001 to December 2006. The data cover 95 grocery supermarket chains, 1,134 distinct stores, and 45,361 distinct UPCs (items). In total, there are over 45 million store–week–UPC observations. There are, on average, 23.5 quarters of transaction data per retailer. The average number of products per store is 4,168.

In our analyses of new product introductions, we focus on new products that are new to the chain (not just new to the store). A product is defined as new to a retail chain when no other store within the chain sold the product in a previous quarter. We use the first six months of 2001 as an initialization period and do not include any products introduced in this window. We identify a total of 29,567 unique items that are introduced to at least one retail chain across the six-year data window. These represent 51.2% of all of the unique items in the data set. Collectively, the new item × retail chain combinations contribute 19.1% of aggregate revenue. As a robustness check, we also repeated the analyses using a 12-month initialization period. The pattern of results did not change.

Table 1. Summary of the IRI Data

Time period	January 2001 to December 2006
Average number of quarters per retail chain	23.5
Number of retail chains	95
Number of stores	1,134
Number of UPCs	45,361
Number of week–UPC–store observations	45,770,048
Avg. number of UPCs per store	4,168

Note. The table reports descriptive statistics for the IRI data set.

We will infer changes in a store's product assortment from the occurrence of transactions. For this reason, we conduct all of our analyses using a calendar quarter as a unit of time. This helps to ensure that we do not incorrectly identify an item as exiting simply because transactions are infrequent.

For each new product introduction (and each store opening), we label the first complete calendar quarter for which we have data as Quarter 1. For example, if a new product was introduced in September, we would label the last calendar quarter of that year (October through December) as Quarter 1 for that product. As a result, each quarter of data used in the analysis includes a complete 13 weeks of data. This ensures that our detection of assortment changes is not confounded by the use of incomplete quarters of data.

We observe whether there are any sales of item i in store s in quarter t. We divide total dollar sales for the quarter by total units sold to calculate average quarterly prices paid at the item × store × quarter level.

Our analysis focuses on new products that have low initial sales. We identify low initial sales events by identifying stores in which the first complete quarter of sales of the new product ranked in the lowest quartile of items in that category × store. More specifically, we repeat this ranking for both dollar sales and unit sales and include items that are in either the lowest quartile of dollar revenues or the lowest quartile of units sold. The results are robust to using either just revenue or just units sold. They are also robust to using a decile threshold, or when including all of the new items in the analysis (the results when including all of the new items are reported in the online appendix). This restriction yields a total of 915,139 store × new item observations.

When initial sales of an item in a new store are low, a retailer's options include adjusting the price or removing the item from that store. Our two outcome measures focus on each type of decision:

- *Price Change* is equal to one if the average price paid for item i in store s in quarter $t+1$ was different by more than 5% in absolute value compared with quarter t (and zero otherwise).[2]
- *Product Exit* is equal to one if item i was sold in store s in quarter t, but was not sold in store s in quarter $t+1$ (and zero otherwise).

The means of these outcome variables (with standard errors (s.e.'s) in parentheses) are 52.04% (0.06%) for *Price Change* and 10.64% (0.03%) for *Product Exit*. These averages are calculated using the new items that had low sales events in their first quarter. Summary statistics for the independent variables used in the analyses are reported in the online appendix.

The frequencies of price changes are qualitatively consistent with previous work using scanner data sets (Nakamura and Steinsson 2008, Anderson et al. 2017, Aparicio et al. 2021). At least some of the price variation captured by the *Price Change* measure is likely to result from temporary discounts. The aggregation of sales to calendar quarters helps to smooth out some of this variation. Other sources of price variation include systematic changes to the regular price or changes to the frequency or depth of temporary discounts.

In our analyses, we contrast how these outcomes vary when the price frictions faced by the retailer are high or low. We start by investigating the timing of price changes on related products.

3. The Timing of Price Changes on Related Products

We will present evidence that the timing of retail price changes exhibits regularities. One regularity is that price changes on related items tend to occur at the same time, where we define related items as items in the same brand, category, and store. If there is a price change on one item, there are also generally price changes on other related items. In contrast, if the price does not change on one item, we generally do not see price changes on other related items.

A second regularity is that the timing of price changes tends to follow annual cycles. If the frequency of price changes in a brand × category × store peaks in one quarter of a year, then price changes are also likely to peak in the same quarter in other years.

The regularities that we identify are not price frictions. Instead, they are likely to result from price frictions, including perhaps managerial and in-store labor constraints. These price frictions appear to make it efficient for retailers to organize their price changes so that they co-occur on related items. We will present evidence that variation in the timing of price changes is at least partly attributable to the timing of wholesale price negotiations between retailers and manufacturers. However, our focus is not on the source of these regularities. Instead, we focus on the relationship between these regularities and retailers' actions if initial sales of a new product are low.

We start by asking whether there are price changes on related products. We then consider the timing of annual price change anniversaries in that brand × category × store. This section concludes with a review of the evidence that wholesale price negotiations between the manufacturer and the retailer contribute to both types of regularities.

3.1. Coordination of Price Changes Within a Brand × Category × Store

We begin by selecting a random pair of products within each brand × category × store (we redraw the selection each quarter). Within each pair, we randomly select one of the items. If this item had a price change in the quarter, then the other item in the pair also had a price change 66.4% (s.e., 0.04%) of the time. In contrast, if the first item did not have a price change in that quarter, then the other item in the pair had a price change just 28.9% (s.e., 0.03%) of the time. The difference in these percentages indicates that items from the same brand × category × store tend to have price changes in the same quarter.

We also asked two related questions. Conditional on an item having a price change in a given quarter, what percentage of the other items in the same brand × category × store have a price change in the same quarter? The distribution of this percentage is reported as a histogram in Figure 1(a). The median of the distribution is 66%, indicating that when at least one product changes price, at least half the time there is a price change on at least 66% of the items in that brand × category × store. Comparing the two ends of the distribution, if there is a price change on the randomly chosen item, then it is common to see price changes on related items, and we essentially never see no price changes on any of the related items.

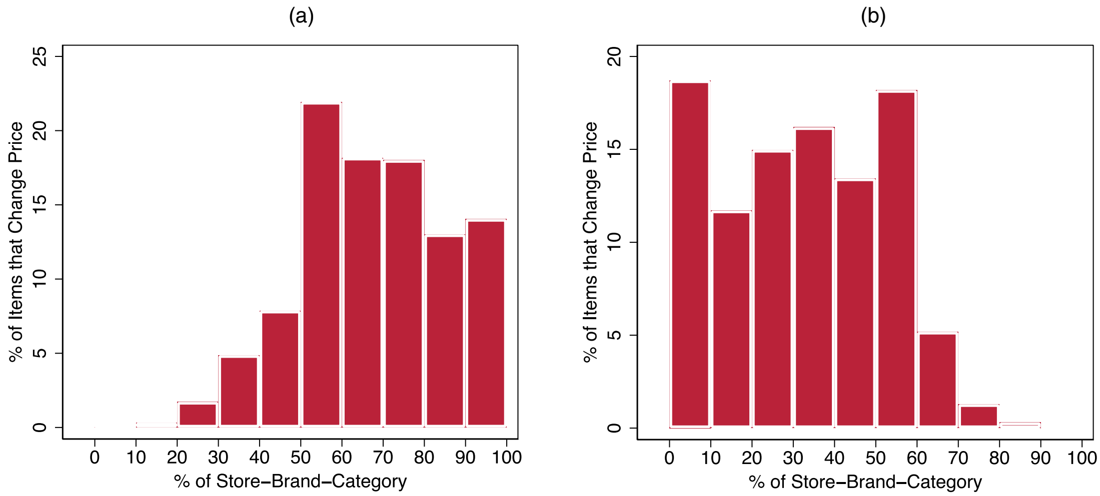
We also ask the reverse: Conditional on the price of an item not changing in that quarter, how many other items in the brand × category × store have a price change? This distribution is reported as a histogram in Figure 1(b). When a given item does not have a price change, then few of the related items have price changes, and we essentially never see price changes on all of the related items.

Together, the distributions in Figure 2 indicate that if there is a price change on one item, there is also generally a price change on related items. In contrast, if the price does not change on one item, we generally do not see price changes on related items.

Further investigation also reveals that the timing of price changes within a brand × product category is also coordinated across different stores within a chain. Price changes on the same items tend to occur at the same time in different stores. This is consistent with findings reported by Aparicio et al. (2021), who also find evidence of considerable price synchronization between supermarket stores. We will later exploit this finding when investigating how retailers respond if sales of an item are low following the opening of a new store.

We next investigate what actions retailers take if initial sales of a new product are low. In particular, we compare the adjustments that retailers make depending on whether there is a price change on other items in that brand × category × store.

Figure 1. (Color online) Coordination of Price Changes Across Related Items in the Same Brand × Category × Store



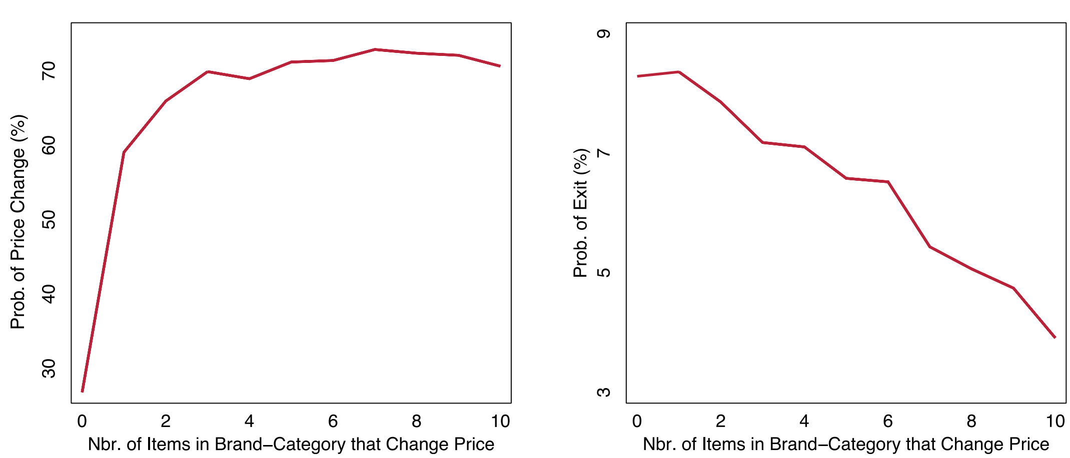
Notes. Panel (a) reports a histogram of the average proportion of items in the brand × category × store × quarter that change prices, conditional on at least one item changing price in that quarter. Panel (b) reports a histogram of the average proportion of items that change prices, conditional on at least one item not having a price change. In both panels, the columns sum to 100%. The unit of analysis in both cases is the average for each brand × category × store across quarters, and the sample sizes are 581,134 (panel (a)) and 593,356 (panel (b)).

3.2. Retailers' Adjustments When Initial Sales Are Low

In panel (a) of Figure 2, we report the probability that the store changes the price after the first complete quarter of new product sales, and in panel (b), we report the probability that the new item is discontinued in the store. The unit of analysis is a new product in a single store. The panels illustrate both types of adjustments according to the number of price changes that quarter on other items in same brand × category × store. This count is capped at 10, and so if more than 10 related items had price changes, we set the value of this count at 10.

We observe two sharply contrasting trends for the two types of adjustments. When no other items change prices, the probability of a price change is just 27%. In contrast, there is an 8% probability that the new product will be discontinued. However, when the prices change on other items in the brand × category × store, the probability of a price change increases sharply, and the probability of exit drops sharply. The change in these effect sizes are very large. The probability of a

Figure 2. (Color online) Retailers' Adjustments When Initial Sales Are Low: Number of Other Items with Price Changes



Notes. Panel (a) reports the probability that the new item has a price change after a low sales event in the first complete quarter of sales. Panel (b) reports the probability that the new item is discontinued after low initial sales in the first quarter. In both panels, the x-axis indicates the number of existing items in the brand × category × store that change prices in the same quarter. The unit of analysis is a new item in a store, and the sample sizes are 815,645 (panel (a)) and 881,028 (panel (b)). The differences in sample sizes arises because we do not observe whether there are price changes on the items that are discontinued. The sample is restricted to new items in the lowest quartile of sales in the brand × category × store.

price change increases from 27% to 71% as the number of related items with price changes increases from 0 to 10 items. The probability of exit drops from approximately 8% to 4% over the same range.

We might be concerned that the related items are just variants of the new item, and that all of these variants have the same price (see, e.g., Anderson et al. 2015, DellaVigna and Gentzkow 2019). Although uniform pricing of variants cannot easily explain why a retailer is less likely to discontinue a new variant when there are price changes on other variants, it could explain why there is a higher probability of a price change on the new variant. Further investigation reveals that there is substantial variation in prices across the related items. Approximately 68% of the items in a brand × category × store have different prices. This suggests that relatively few of the related items are same-priced variants. Moreover, the results are not sensitive to omitting observations in which at least one other product in the brand × category × store × quarter had the same price. In the online appendix, we repeat Figure 2 when excluding these observations. The pattern of findings is unchanged.[3]

The findings in Figure 2 include a comparison across new items. Therefore, a possible interpretation is that there are some categories, perhaps the "more important" categories, on which the retailer prioritizes price changes. Retailers may change prices more frequently in more important categories. It is also possible that they are more likely to respond to low initial sales on new items in these categories by changing prices instead of discontinuing the new items. To address this alternative explanation, we used ordinary least squares (OLS) to estimate the following fixed effects model:

$$Y_{i,s,t} = \alpha + \beta_1 \mathit{Number\ of\ Other\ Products}_{i,s,t} + \boldsymbol{\gamma}\ \mathbf{Chain{:}Quarter} + \boldsymbol{\omega}\ \mathbf{Item} + \varepsilon_{i,s,t}. \tag{1}$$

The unit of analysis is a new item × store. We estimate the model separately using each of our two outcome variables. The *Number of Other Products* variable is a count of the number of existing items in the same brand × category × store as item i that had a price change following the first complete quarter of sales of item i. The **γ Chain:Quarter** and **ω Item** terms represent complete sets of quarter × chain–level and item-level fixed effects. The quarter × chain fixed effects distinguish each of the sequential quarters across the data period (rather than just the four calendar quarter within a year). We cluster the standard errors at the item × chain level. In the online appendix, we also report alternative clusters of the standard errors.

The model is a linear probability model, and the coefficient of interest, β_1, estimates how the probability of each type of retailer action varies according to the number of existing items in the brand × category × store that had price changes. The item-level fixed effects completely control for any item-level variation in these probabilities. This ensures that the coefficients of interest are not influenced by some items receiving priority over other items. Instead, β_1 is identified by variation within an item across stores in the number of related items that had a price change.[4]

The findings, which are reported in the first row of Table 2, repeat the pattern in Figure 2. We see a strong relationship between the decision to change prices and the number of other items in the brand × category × store that have a price change. When there are other items with price changes, the probability of a price change is higher, and the probability the new item will be discontinued is lower. The inclusion of item-level fixed effects confirms that the effect survives even when controlling for the relative "importance" of the new items.

We also investigated a range of alternative specifications, including

- using a binary indicator of whether any other items in the brand × category × store had a price change,
- using the percentage of other items in the brand × category × store that had a price change (measured from zero to one), and
- using a nonparametric specification, in which we estimated separate coefficients for the number of other products in the brand × category × store that had a price change.

The findings for the first two of these alternative specifications are reported in the other rows of Table 2 (model specifications and variable definitions are all provided in the online appendix). They repeat the pattern of findings reported for Equation (1). The effect sizes are notable; in the *Percentage of Other Products* model, an increase from 0% to 100% in the percentage of other products in the brand × category × store that had a price change is associated with a 33.14% increase in the probability of a price change and a 3.25% reduction in the probability of the new product exiting.[5]

The nonparametric specification uses the following model:

$$\begin{aligned} Y_{i,s,t} = \alpha &+ \beta_1 \mathit{One\ Other\ Product}_{i,s,t} \\ &+ \beta_2 \mathit{Two\ Other\ Products}_{i,s,t} \\ &+ \beta_3 \mathit{Three\ to\ Five\ Other\ Products}_{i,s,t} \\ &+ \beta_4 \mathit{More\ Than\ Five\ Other\ Products}_{i,s,t} \\ &+ \boldsymbol{\gamma}\ \mathbf{Chain{:}Quarter} + \boldsymbol{\omega}\ \mathbf{Item} + \varepsilon_{i,s,t}. \end{aligned} \tag{2}$$

In this specification, we replaced the *Number of Other Products* variable in Equation (1) with four binary variables identifying the number of other products that had price changes in that brand × category × store (for that observation). The coefficients for these four

Table 2. Retailers' Adjustments When Initial Sales Are Low: Number of Other Items with Price Changes

	Price change	Product exit
Primary model		
Number of Other Products	3.81%** (0.05%)	−0.47%** (0.01%)
Robustness checks		
At Least One Other Product	43.50%** (0.24%)	−2.06%** (0.10%)
Percentage of Other Products	33.14%** (0.28%)	−3.25%** (0.11%)
Price change anniversaries		
Price Change Anniversary Coincides	8.57%** (0.23%)	−0.45%** (0.10%)
R^2		
Equation (1)	0.27	0.31
Equation (1a) (online appendix)	0.34	0.31
Equation (1b) (online appendix)	0.27	0.31
Equation (3)	0.20	0.11

Notes. The table reports the coefficients of interest from estimating Equation (1) (and its robustness specifications) and Equation (3) using each dependent variable (*Price Change* or *Product Exit*). Each coefficient is from a separate model. Equations (1a) and (1b) are described in the online appendix. The unit of analysis is a new item × store. The sample sizes for Equations (1), (1a), and (1b) are 715,924 observations (*Price Change*) and 600,207 observations (*Product Exit*). The sample sizes for Equation (3) are 293,263 observations (*Price Change*) and 209,151 observations (*Product Exit*). The sample is restricted to new products in the lowest quartile of sales in the brand × category × store and to products that have variation in price change or exit. Standard errors clustered at the chain × item level are in parentheses. Alternative clusters are reported in the online appendix.

**Significantly different from zero at $p < 0.01$.

variables can be interpreted as the change in the probability of each outcome compared with when there are no other items with price changes in that brand × category × store. Compared with Equation (1), this specification allows more flexibility in the relationship between the outcome variable and the number of other items with price changes. We report detailed findings in the online appendix and illustrate the coefficients of interest in Figure 3. The data point for "zero other items with a price change" was not estimated and is simply provided as a benchmark.

The findings reveal a clear pattern. When more items in the brand × category × store have price changes, then new products with low initial sales are more likely to have adjustments and are less likely to be discontinued. The effects are monotonic and very large. The probability of a price change is over 75% higher if more than five other items have price changes, compared with when no other items have price changes, whereas the probability the new product will be discontinued is almost 10% lower (see the detailed findings in the online appendix).

In the online appendix, we also report an additional array of robustness checks, including (a) using a conditional logistic model instead of OLS, (b) investigating the robustness of the linear probability model using the conditions in Horrace and Oaxaca (2006), and (c) including all new items, rather than just new items with low initial sales. The pattern of findings is reassuringly robust to each of these alternatives. We also repeat the same robustness checks for the analyses in the remaining sections of this paper and report the findings in the online appendix.

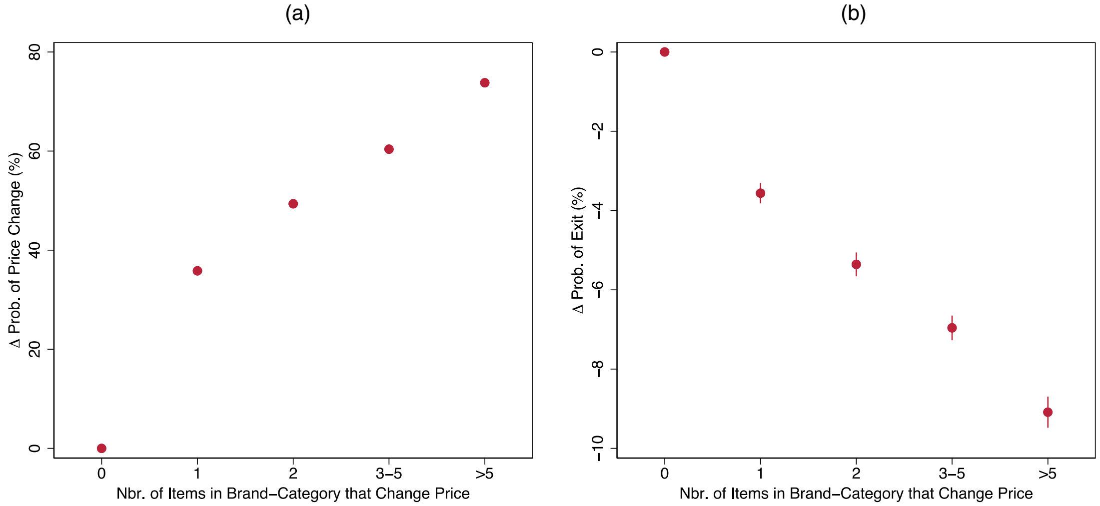
In our next set of analyses, we use a different way of measuring the timing of retailers' price changes. This second approach exploits regularities in the timing of price changes across years.

3.3. Price Change Anniversaries

For many products, price changes appear to exhibit annual cycles, peaking in the same calendar quarter each year. The timing of these peaks is typically the same for items in the same product category that share the same brand. However, the timing of the peaks tends to vary across retailers and brands.

To identify the peaks in these cycles, we use the timing of price changes for all of the items in each brand × category × store, excluding the new product itself. In particular, for each brand × category × store, we identify the calendar quarter in which price changes are most common (excluding the new product itself). The "anniversary" quarter is the calendar quarter in which the prices of other items in that brand × category × store are most likely to be different from those in the previous calendar quarter.[6] In the online appendix, we report the percentage of brand × category × stores that have price change anniversaries in each of the four calendar quarters. More price change anniversaries occur in the fourth quarter than in the other three calendar quarters, but the evidence confirms that price change anniversaries are distributed throughout the year.

Figure 3. (Color online) Coefficients from Nonparametric Specification



Notes. The figures report the coefficients of interest from Equation (2). This nonparametric specification estimates separate coefficients for the number of other products with price changes (in that brand × category × store). The data point for "zero other items with a price change" was not estimated and is simply provided as a benchmark. Panel (a) reports the change in the probability that the new product has a price change after a low sales event in the first complete quarter of sales depending on the number of other products that change price. Panel (b) reports the change in the probability that the new item is discontinued after low initial sales in the first quarter. The sample sizes are 715,924 observations (*Price Change*) and 600,207 observations (*Product Exit*). Vertical lines indicate 95% confidence intervals.

To illustrate the stability of annual price change cycles, we identify price change anniversaries in a brand × category × store using data from the first four years of the data period. We use the last two years of the data period as a holdout sample and compare the frequency of price changes in anniversary and nonanniversary quarters in the holdout. On average, 69.0% (0.08%) of items have price changes in anniversary quarters, compared with just 30.0% (0.06%) of items in nonanniversary quarters (standard errors in parentheses).[7]

We also calculate how often the timing of a new product entry "coincides" with the price change anniversary for that brand × category × store. We define the timing as coinciding if the price change anniversary occurs immediately after the first complete quarter of sales for the new product.[8] On average, the price change anniversaries coincide with the new product introduction 32% of the time. We will use these price change anniversaries to further study retailers' actions when initial sales of the new product are low. In particular, we estimate the following model:

$$Y_{i,s,t} = \alpha + \beta_1 \mathit{Price\ Change\ Anniversary\ Coincides}_{i,s,t} + \boldsymbol{\gamma}\ \mathbf{Chain{:}Quarter} + \boldsymbol{\omega}\ \mathbf{Item} + \varepsilon_{i,s,t}. \tag{3}$$

Equation (3) is the same as Equation (1), with the exception that we replace *Number of Other Products* with *Price Change Anniversary Coincides*. The new variable is a binary indicator identifying whether the price change anniversary occurs immediately following the first complete quarter of sales for the new product. We estimate Equation (3) using low initial sales events and report the findings in Table 2.

The findings reveal a relationship between how a retailer responds to low initial sales of a new product and whether the timing of the initial sales coincides with the annual price change anniversary in that brand × category × store. If the timing coincides, the retailer is 8.57% more likely to change prices, compared with when the timing does not coincide. In contrast, the probability that the item is discontinued is reversed. The probability a new item will be discontinued is 0.45% lower when the timing coincides with the price change anniversary, compared with when the timing does not coincide. Together these findings indicate that when initial sales of a new product coincide with the anniversary of price changes in that brand × category × store, retailers are more likely to adjust the price of the new item and are less likely to discontinue it.

3.4. The Timing of Retail Price Changes

We have presented evidence that price changes tend to occur at the same time for items within a brand × category × store and in the same quarter each year. One explanation for the timing of retail price changes is the timing of wholesale price negotiations with vendors. Support for this explanation can be found in the existing literature, which documents the pass-through of wholesale price changes to retail prices. For example, Anderson et al. (2017) show that following a wholesale price change, there is a sharp and immediate change in retail prices. Similar findings are reported by Eichenbaum et al. (2011) and McShane et al. (2016).

There is also evidence in the literature that wholesale price changes occur on annual cycles. Our own discussions with managers of a large national retail reveal that they typically negotiate wholesale prices with an individual vendor once a year, and that these negotiations typically occur at the same time each year. Anderson et al. (2017) also report that retailers and vendors typically engage in an annual planning process. They describe this process in detail. These negotiations encompass all of the items that the manufacturer sells in a category. The negotiations yield a plan for the year, including wholesale price changes and trade promotions. Because price changes are complex, once negotiated, these plans are "sticky," and will often not change until the following year's planning cycle. This process is consistent with our evidence that retail price changes have annual cycles and are coordinated within a brand × category.

We can also investigate the relationship between wholesale price changes and retail price changes using our quarterly price change measures. We used data from the same national chain of drugstores that provided data for Anderson et al. (2017) and McShane et al. (2016). This retailer associates a wholesale price with each transaction (see the online appendix for a description of the data). We used the procedures described in Section 2 to calculate the average wholesale price and average retail price paid in each quarter, and then used these averages to identify price changes between quarters.

Wholesale price changes on related items tend to occur in the same quarter. To illustrate, we randomly selected (within each quarter) pairs of items in the same brand × category × store. We then randomly selected one item in the pair. If this one item had a wholesale price change that quarter, then the other item in the pair also had a wholesale price change 54.7% (s.e., 0.30%) of the time. In contrast, if the first item did not have a wholesale price change in that quarter, then the other item in the pair had a wholesale price change just 2.9% (s.e., 0.03%) of the time.

There is also strong evidence that wholesale price changes occur at the same time each year. We used the first three years of data to identify the anniversary quarter in each brand × category × store. The probability of a wholesale price change on an item in the fourth year was 3.53% (s.e., 0.11%) in the anniversary quarter, and only 2.35% (s.e., 0.05%) in the nonanniversary quarters. We conclude that the same two regularities that we observe in the IRI retail price data also arise in this retailer's wholesale price data.

Next, we investigate the relationship between the timing of wholesale price changes and retail price changes at this retailer. Retail prices changed in 73.7% (s.e., 0.14%) of the quarters in which the wholesale price changed (averaging across items and stores). This reduced to 41.2% (s.e., 0.04%) in quarters without a wholesale price change. We also used this drugstore's data to separately identify the anniversary quarter for wholesale price and retail price changes for each item × store. These represent the calendar quarters with the most frequent price changes, calculated using all of the items in that brand × category × store (except the focal item). In terms of timing, the wholesale price and retail price anniversaries coincide in 39.4% (s.e., 0.24%) of the item × store observations. If these anniversaries were unrelated in terms of timing, we would expect them to coincide just 25% of the time. These patterns are what we would expect, if the timing of wholesale price changes contributes an important source of variation in retail price changes.

Although wholesale price changes appear to contribute to the timing of price changes on related items, this clearly not the only source of variation in the timing of price changes. In particular, it is possible that we might see price changes on related items because the related items also have low sales. However, as we discussed at the start of this section, our focus is not on explaining why prices change on related items. Instead, we show that retailers' responses to low initial sales of a new product are different according to the timing of price changes on related products. Whatever the reason for the price change on the related products, it appears that a retailer is less likely to discontinue a new item, and more likely to adjust the price, when it is also changing the price of related items.

3.5. Summary

We have used the timing of price changes to evaluate how retailers respond to low initial sales of a new product. In particular, we measure whether the timing of a new product introduction coincides with (a) price changes on other items in that brand × category × store and (b) the annual anniversary of price changes in that brand × category × store.

If sales of an item are low in the first quarter after the new product is introduced, and the timing coincides with price changes on other items in that brand × category × store, or the annual anniversary of price changes in that brand × category × store, then there is a sharp increase in the likelihood that the retailer will adjust the price of the new product. In contrast, if the timing does not coincide, then the retailer is less likely to adjust the price of the new product, and instead it is more likely that the retailer will discontinue the product. In the next section, we consider two other settings in which retailers may be reluctant to change prices.

4. Item Pricing Requirements and 99¢ Price Endings

In this section, we consider item pricing requirements and 99¢ price endings. We begin with item pricing requirements.

4.1. Item Pricing Requirements

In the early 1970s, a focus on "truth in labeling" prompted some states to require that retailers put price stickers on every individual package of the items that they sell. The goals of these laws were to ensure that customers were more informed about prices when making their purchasing decisions, and to enable customers and cashiers to better detect pricing mistakes (Bergen et al. 2008).

Item pricing requirements greatly increase the amount of in-store labor required to change the price of an item. Rather than just changing the shelf label and a variable in the point-of-sale (POS) system, employees must now change the physical sticker on every package on the shelf. Levy et al. (1998) detail 15 additional steps in the price change process due to item pricing laws, including removing the item from the shelf, removing the old price sticker, applying the new price sticker, and returning the item to the shelf. They estimate this requires an additional 270 seconds per product in a typical store (assuming the store stocks 28 units of the item). Notably, this additional friction on price changes arises only in states that have item pricing requirements.

Levy et al. (1998) and Bergen et al. (2008) both studied the impact of item pricing requirements on the frequency of retail price changes. Levy et al. (1998) compared five U.S. supermarket chains. Four of the chains were located in states that did not require item pricing. These retailers changed 12%–17% of their prices each week. In contrast, the fifth retailer was located in a state that required item pricing. This retailer changed just 6.3% of its prices each week.

Bergen et al. (2008) studied supermarket chains in the tristate area of New York, Connecticut, and New Jersey. At the time of their study, New York had item pricing laws, New Jersey did not, and Connecticut required item pricing but had an exception for retailers with electronic shelf labels. They found consistent evidence that item pricing requirements increased prices by 8.0% to 9.6% per item on average. In Connecticut, these price differences were partially offset when retailers had electronic shelf label systems (which introduce their own costs). They also measured the size and frequency of pricing mistakes and concluded that the costs that item pricing laws impose on customers greatly outweigh any benefits of reducing pricing mistakes.

We interpret item pricing requirements as a form of price friction and investigate how the presence (or absence) of these laws affect how retailers respond when a new product has low initial sales. The list of states that require item pricing has varied over time, but during the period of our data included California, Connecticut, Illinois, Massachusetts, Michigan, New Hampshire, New York, North Dakota, and Rhode Island (Bergen et al. 2008).

We construct a binary indicator to identify the stores in the IRI data that were subject to item pricing requirements (*Item Pricing Required*). Overall, 46% of the new product × store observations in our sample were in states with item pricing requirements, whereas the remainder were in states without item pricing requirements.

We first present preliminary evidence that, in the IRI data, item pricing requirements are associated with less frequent price changes. We focus on existing products (and existing stores) and restrict attention to retail chains that had stores in both states with and states without item pricing requirements. For each chain × quarter combination, we randomly select 50 store × item observations from stores located in states with item pricing requirements and a separate sample of 50 observations from stores in states without item pricing requirements. This yields two samples, each with 12,550 observations. Using the *Price Change* measure that we introduced in Section 2 (and use throughout this paper), we separately calculate the average probability of a price change between the focal quarter and next quarter, using the observations in each sample. The average probability of a price change is 50.17% (s.e., 0.45%) in the observations without item pricing requirements, but only 48.35% (s.e., 0.45%) in the observations with item pricing restrictions. The 1.82% (s.e., 0.63%) difference is significantly different from zero ($p < 0.01$). This finding is consistent with the conclusions in Levy et al. (1998) and Bergen et al. (2008) that item pricing requirements represent a price friction that reduce the frequency of price changes. For completeness, we also estimate an OLS model using all of the available data, including both chain × quarter and item fixed effects. These findings are reported in the online appendix and confirm that, in the IRI data, item pricing requirements are associated with less frequent price changes.

Next, we investigate the relationship between item pricing requirements and how retailers respond to low initial sales of new items. In particular, we modify Equations (1) and (3) using our binary indicator *Item Pricing Required*:

$$Y_{i,s,t} = \alpha + \beta_1 Item\ Pricing\ Required_{i,s,t} + \boldsymbol{\gamma}\ \mathbf{Chain{:}Quarter} + \boldsymbol{\omega}\ \mathbf{Item} + \varepsilon_{i,s,t}. \quad (4)$$

We estimate this equation separately using OLS for each of our two outcome measures. The estimation sample again restricts attention to new products with

Table 3. Item Pricing Requirements and 99¢ Price Endings

	Price change	Product exit
Item Pricing Requirements (Equation (4))	−0.72%* (0.29%)	0.36%* (0.16%)
Price Ending (Equation (5))	−6.51%** (0.37%)	0.77%** (0.16%)
R^2		
Equation (4)	0.22	0.32
Equation (5)	0.22	0.32

Notes. The table reports the coefficients of interest from estimating Equations (4) and (5) using each dependent variable (*Price Change* or *Product Exit*). Each coefficient is from a separate model. The unit of analysis is a new item × store. The sample sizes are 717,944 observations (*Price Change*) and 710,286 observations (*Product Exit*). The sample is restricted to new products in the lowest quartile of sales in the brand × category × store and to products that have variation in price change or exit. Standard errors clustered at the chain × item level are in parentheses. Alternative clusters are reported in the online appendix.

*Significantly different from zero at $p < 0.05$; **significantly different from zero at $p < 0.01$.

low initial sales, and we report the coefficient of interest (β_1) in Table 3.

The findings reveal that if first-quarter sales of a new product are low, retailers are less likely to adjust the price when the store is in a state that requires item pricing. Instead, there is a higher probability that the retailer will discontinue the new product. These findings are consistent with the findings we reported in the previous section. In settings that we associate with larger price frictions, we see a lower probability of price changes and a higher probability that the new product will be discontinued. We next investigate whether we see observe a similar pattern with price endings.

4.2. 99¢ Price Endings

There are extensive literatures examining both retailers' use of 99¢ price endings (e.g., $2.99), and their impact on price stickiness. We start by briefly reviewing the literature on the prevalence and then discuss the literature describing the contribution of 99¢ price endings to price stickiness.

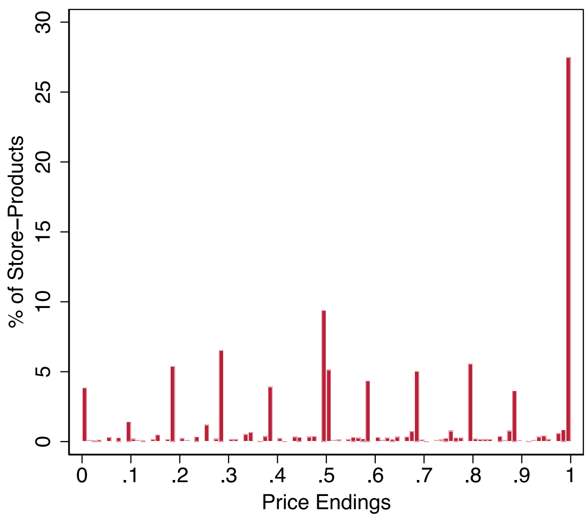
As early as 1954, researchers have documented that retailers are more likely to use "9" as a price ending than any other digit (Rudolph 1954, cited in Stiving and Winer 1997). More recent examples include Levy et al. (2011, 2020) and Anderson et al. (2015). Explanations have focused on the sales impact of price endings, with many studies reporting significant kinks in the demand curve around "9" or "99" price endings (Nagle 1987, Blattberg and Neslin 1990, Schindler and Kibarian 1996, Stiving and Winer 1997, Anderson and Simester 2003). The reason for the kink in the demand curve is less clear. Explanations have included customers rounding down and ignoring the last digit(s), customers prioritizing left-hand digits when comparing prices, and price endings operating as a cue to signal price or quality information. Other explanations for why retailers prefer to use a 99¢ price ending have focused on the implications for operations. By forcing clerks to make change, retailers may deter employees from pocketing money without entering the transactions into the POS system (Schindler and Kirby 1997).

The literature documenting the contribution of "9" endings to price stickiness is also extensive. For example, this is one of the 12 explanations for price stickiness that Blinder et al. (1998) evaluate in their survey of why firms are reluctant to change prices. Of the 17 retailers they surveyed, 15 believed that their customers were affected by price endings, and many of these retailers indicated that price endings contributed to their decisions to change prices. Kashyap (1995) studied catalog prices and found, after controlling for cost shocks and competitors' prices, that price endings could significantly reduce the probability of a price change. Levy et al. (2011) extended this analysis using both a large sample of retail scanner data and a second sample of internet prices for 474 consumer electronics. They reported that in both data sets, prices were significantly less likely to change if the current price ended in "9." Further evidence that price endings reduce the probability of a price change is reported by Anderson et al. (2015). Using a sample of data from a chain of convenience stores, they estimate how often the retail price changes following a change in the wholesale price. They find that the price is approximately 8.3% less likely to change if the price ends in 99¢. Similar stickiness effects in price changes or pass-through are reported by Knotek (2008, 2011) and Aparicio and Rigobon (2020).

Using the first week of sales data in each store × product, we begin by reporting the distribution of price endings in the IRI data set. Figure 4 presents a histogram of the price endings, represented by the last two digits in each price. We see that 27% of the prices in the IRI data set end in 99¢.

We next present evidence that, in the IRI data, 99¢ price endings are associated with less frequent price changes. Similar to our analysis of item pricing requirements, we again focus on existing products and

Figure 4. (Color online) Distribution of Price Endings



Notes. The figure shows the frequency of price endings in the first week of data for each store × product, including new and existing products. The columns add to 100%. The unit of analysis is a store × item, and the sample size is 12,265,707 observations.

existing stores. For each chain × quarter combination, we randomly selected 50 store × item observations that had 99¢ price endings (in the focal quarter) and a separate sample of 50 observations that did not have 99¢ price endings. We separately calculated the average probability of a price change between the focal quarter and next quarter, using the 88,750 observations in each sample. The average probability of a price change was 45.28% (0.17%.) in the observations without 99¢ price endings and only 20.42% (0.14%) in the observations with 99¢ price endings (standard errors in parentheses). The 24.86% (0.22%) difference is significantly different from zero ($p < 0.01$). This finding is consistent with the evidence elsewhere in the literature that items with 99¢ price endings have less frequent price changes. For completeness, we again estimated a fixed effects OLS model using all of the available data. These findings are reported in the online appendix and confirm that 99¢ price endings are associated with less frequent price changes.

We construct a binary indicator (*Price Ending*) identifying whether the average price throughout the first complete quarter of a new product's sales ended in 99¢. We used this variable as a measure of price frictions in our fixed effects model:

$$Y_{i,s,t} = \alpha + \beta_1 Price\ Ending_{i,s,t} + \boldsymbol{\gamma}\, \mathbf{Chain{:}Quarter} + \boldsymbol{\omega}\, \mathbf{Item} + \varepsilon_{i,s,t}. \quad (5)$$

Equation (5) was estimated using the same estimation sample as the three previous equations, and the results are reported in Table 3. The results are consistent both with our earlier findings, and the previous literature establishing that price endings can contribute to price frictions. When initial sales of a new product are low, retailers are less likely to adjust the price if it currently has a 99¢ ending. The size of the effect (6.51%) is similar in magnitude to the 8.3% lower probability of a price change reported by Anderson et al. (2015). When the new product has a 99¢ price ending, we also see there is a significantly higher probability the new product will be discontinued if initial sales are low. As a robustness check, we also estimated a model in which we identified whether the price in the first month of sales ended in 99¢. This alternative specification yielded a similar pattern of results.

4.3. Summary

We replicated our analysis of retailers' adjustments when initial sales of new products are low using two different types of variation. They include variation in item pricing requirements for stores located in different states and variation in the use of 99¢ price endings. The pattern of results replicates the findings in the previous section, where we showed that retailers' responses to low initial sales varied according to the timing of price changes on related items.

In the next section, we investigate the robustness of the findings by studying retailers' actions under a different source of uncertainty: the opening of a new store.

5. Price and Assortment Adjustments After the Opening of a New Store

Different stores within the same grocery chain often offer different assortments and charge different prices for the same products. Therefore, when opening a new store, the retailer must choose products and prices for the new store. However, because the store is new, local demand conditions will often be uncertain. For this reason, new store openings provide a valuable opportunity to learn how retailers adjust prices and product assortments. We will again use the IRI scanner data set and study how retailers respond if initial sales of an item are low in a new store.

We identify store openings by applying a series of filters. We consider stores whose opening date occurs after the first two quarters of 2001 and before the last two quarters of 2006. From this list of potential events, we restrict attention to stores that have at most one opening date. We exclude store openings where the same chain has more than two store openings in the same week in the same city. This helps to ensure that the store openings are not associated with mergers or acquisitions (see Kruger and Pagni 2009). Finally, in order to avoid overweighting events from a single chain, we do not include more than 10 store openings from any single chain. The store openings are randomly selected, while maximizing geographic coverage (to avoid selecting too many events from a given chain in the same city). Together these filters result in the identification of 221 qualifying store openings (and the omission of approximately 120 store openings).[9] Our analysis will focus on these 221 store openings.

We focus on products that have low initial sales in the first complete calendar quarter of sales after the *new store opened* (and we report findings for all of the products in the new store in the online appendix). As with the new product analysis, we identify low initial sales as products with sales in the lowest quartile in the store × category (see Section 2 for a more detailed description). This yields a total of 123,580 new store × item observations. The averages of our two outcomes measures across these observations are 45.48% (0.16%) for *Price Change* and 17.68% (0.11%) for *Product Exit*, with standard errors in parentheses. Recall that both of our outcome measures are defined at the item × store level. For example, *Product Exit* measures whether the item was discontinued at the focal store (not in the entire chain).

We focus on the same three types of variation that we focused on for new products. The item pricing requirement and price ending measures are constructed using an approach identical to that for the new product analyses. For the timing of price changes, we adjust our measures of price change anniversaries and price changes on related items.

Recall that in our analysis of new products, we identified price change anniversaries for an item by looking across years and identifying the calendar quarter for which price changes are most frequent in that brand × category × store. For new stores, we have no prior years available to help identify the price change anniversaries at those stores. Fortunately, the timing of the price change anniversaries is very strongly coordinated across stores within a retail chain. As we discussed in Section 3, similar evidence of synchronization has also been found in other data sets (see Aparicio et al. 2021). Therefore, instead of identifying price change anniversaries at the focal store, we identify the anniversaries at the chain level. In particular, we identify the anniversary of price change on an item by identifying the quarter in which price changes are most common for that item using all of the stores in the chain.[10]

In our new product analyses, the *Number of Other Products* measure counts the number of other items in the brand × category that had a price change at the focal store (in the quarter after observing the first complete quarter of sales). In this analysis of new store openings, we instead count the number of other stores that have a price change on the focal product. We label this new measure *Number of Other Stores*. We use these measures to reestimate Equations (1), (3), (4), and (5) and report the findings in Table 4. The standard errors are again clustered at the chain × item level, with alternative clusters reported in the online appendix.

The pattern of findings replicates the results from our analyses of new products. For our two measures of the timing of price changes (*Number of Other Stores* and *Price Change Anniversary Coincides*), higher values are associated with smaller price frictions. For our other two measures, higher values are associated with larger price frictions. The pattern of coefficients consistently indicates that larger price frictions coincide with a lower probability that retailers will adjust prices when initial sales in a new store are low, and an increased likelihood that the retailer will discontinue the product at that store.

Table 4. Price and Assortment Adjustments After the Opening of a New Store

	Price change	Product exit
Number of Other Stores (Equation (1))	4.79%** (0.05%)	−0.76%** (0.04%)
Price Change Anniversary Coincides (Equation (3))	21.03%** (0.39%)	−9.61%** (0.32%)
Item Pricing Requirements (Equation (4))	−6.99%** (1.82%)	2.37%† (1.38%)
Price Ending (Equation (5))	−10.89%** (0.65%)	2.89%** (0.54%)
R^2		
Equation (1)	0.36	0.16
Equation (3)	0.23	0.20
Equation (4)	0.20	0.19
Equation (5)	0.21	0.20

Notes. The table reports the coefficients of interest from estimating Equations (1), (3), (4), and (5) using each dependent variable (*Price Change* or *Product Exit*). Each coefficient is from a separate model. The unit of analysis is a new store × item. The sample is restricted to new products in the lowest quartile of sales in the brand × category × store and to products that have variation in price change or exit. In Equation (1), the sample sizes are 84,541 observations (*Price Change*) and 63,948 observations (*Product Exit*). In Equation (3), the sample sizes are 84,541 observations (*Price Change*) and 64,661 observations (*Product Exit*). In Equations (4) and (5), the sample sizes are 84,541 observations (*Price Change*) and 84,985 observations (*Product Exit*). Standard errors clustered at the chain × item level are in parentheses. Alternative clusters are reported in the online appendix.

†Significantly different from zero at $p < 0.10$; **significantly different from zero at $p < 0.01$.

We replicated Table 4 using the same battery of robustness checks that we used for the new product analysis in Sections 3 and 4. We observe the same pattern of findings, although the statistical significance of the item pricing–product exit model varies. In addition, we reestimated all of the results when identifying items with low initial sales in the new store by comparing them with sales in a matched benchmark store (specific to each new store). The matching process is described in detail in the online appendix, together with the findings for each of these robustness checks. The pattern of findings remains unchanged.

5.1. Summary

The replication of the findings using a different type of retailer decision is reassuring. Although new products and new stores both introduce uncertainty for a retailer's pricing and product assortment decisions, the nature and extent of this uncertainty are different. Introducing a new store exposes the retailer to uncertainty about customers' preferences in the local market and how those preferences differ from preferences in other markets in which the retailer has existing stores. In contrast, introducing a new product creates uncertainty around how customer preferences for the new product will vary from those for existing products that it already sells. The differences in these sources of uncertainty could potentially affect how a retailer responds when initial sales are low. Our findings indicate that despite the differences in these two settings, the relationships that we document between price frictions and retailers' actions are similar. Larger price frictions are associated with a lower probability that retailers will adjust the price and a higher probability that the item will be discontinued.

6. Discussion and Conclusions

We have studied the relationship between price frictions and retailers' adjustments when initial sales of new products are low. The findings reveal that when price frictions are high, retailers are less likely to adjust prices and more likely to discontinue the new products (compared with when price frictions are low). We then replicate this pattern of findings by observing retailers' actions after the first complete quarter of sales in new stores.

Our analysis has focused on three types of variation. These include whether a store is located in a state that requires item pricing and whether an item has a 99¢ price ending. The third type of variation focuses on the timing of price changes, which we identify using two approaches. The first approach counts the number of price changes within the same brand × category × store. The second approach compares price changes across years and identifies the calendar quarter with the most frequent price changes for each brand × category × store.

Our data do not contain experimental variation in price frictions, and it would be difficult to randomly introduce this type of variation. For example, it is unlikely that a retailer would be willing to randomly vary whether it puts price stickers on every package, or the timing of annual price changes in different stores. For this reason, throughout our analyses, we have been careful to avoid making causal claims. Instead, we have framed the relationships as mere associations. We believe that this is appropriate when considering each analysis in isolation, because (with the possible exception of the item pricing requirement) each source of variation is endogenous. For example, the timing of price changes and the introduction of new products are both controlled by the retailer. It is possible that factors that contribute to whether scheduled price changes and new product introductions coincide could also contribute to how a retailer responds to low initial sales. Similarly, the factors that influence a retailer to use 99¢ price endings on a new product could influence a retailer's response to low initial sales.

It is more difficult to identify a similar endogeneity argument for the item pricing results. Many of the retailers have stores in multiple states, including states both with and without item pricing requirements. Because we include chain-quarter fixed effects in our analyses, the coefficients of interest are identified by variation across stores within a chain-quarter. The variation is therefore attributable to state government decisions about whether to pass item pricing laws. It may be possible to construct an argument that explains how variation in these state government decisions is related to retailers' responses to low initial sales. However, it seems that such an argument would be less plausible than a conclusion that larger price frictions influenced retailers' decisions not to respond with a price change, and instead to respond by discontinuing the item.

This conclusion is further supported by the differences in the sources of variation that we have studied. As we discussed, the timing of scheduled price changes is likely to be influenced by the timing of wholesale price negotiations with vendors. The use of 99¢ price endings is likely to reflect retailers' preferences for exploiting kinks in the demand curve around this price point. The use of 99¢ price endings therefore depends on how close the retailer's (otherwise) preferred price is to this price ending. Finally, as we discussed, the variation in item pricing restrictions reflects variation in decisions by state governments. These three sources of variation are distinctly different. Although it may be possible to construct three separate endogeneity arguments to explain each set of findings, the differences in the sources of variation make it less likely that all three explanations hold collectively. Instead, the alternative argument that price frictions contribute to retailers' responses becomes increasingly plausible.

If manufacturers and retailers recognized the relationship between the timing of new product introductions and the scheduling of price changes, and they believed this relationship was causal, it seems likely that at least some of them would try to adjust the timing of their new product introductions. Although manufacturers often introduce new products at the same time at different retailers, they may instead want to adjust the timing of new product introductions at some retailers. This could provide more price flexibility if initial sales are low.

We see two important avenues for future research. First, we hope that our findings will stimulate research contrasting how other types of price frictions influence product assortments. This might include comparing the impact of scarce managerial capacity with scarce in-store labor capacity. Second, we have studied how the impact of price frictions can extend beyond pricing decisions to impact product assortment decisions. Future research could continue this path to explore the impact on other types of marketing decisions.

Acknowledgments

The authors thank Emi Nakamura, Catherine Tucker, Yuting Zhu, Juanjuan Zhang, and the review team for helpful comments. The authors also thank IRI for providing the data used in this study (the IRI academic data set). All estimates and analyses in this paper based on IRI data are by the authors and not by IRI.

Endnotes

[1] The brand is defined using the "L5" field in the "parsed stub files" in the IRI academic data. We identify chains using the "YearXChain" field. The chain identifiers are masked each year, and we cross-reference the store with the corresponding chain identifier consistently over time. A chain, as defined in the IRI data, is not typically market specific.

[2] A price change is defined as $\frac{p_{i,t+1}-p_{i,t}}{p_{i,t}}$. The results are robust to using a smaller (3%) threshold or a larger (6%) threshold.

[3] When counting the number of related items that had price changes, we had to decide how to treat observations when there were no items in the same brand × category × store (in that quarter). We reasoned that there was no price change on related items for that observation, and so treated the number of other items with changes as zero. As a robustness check, we also repeated the analysis with these observations omitted. Reassuringly, the pattern of findings and magnitude of the effects were also very similar to the findings in Figure 2. (In the online appendix, we report a version of Figure 2 in which we omitted these observations.)

[4] The inclusion of item-level fixed effects also means that any items for which there is no variation in the dependent variable do not contribute to the estimation of the coefficient of interest (β_1). For this reason, we omit these items from the analysis. This does not change the results, but it does contribute to variation in the sample sizes in this model compared with our subsequent analyses. The sample sizes also vary when using *Price Change* or *Product Exit* as the dependent variable. This is because the *Price Change* measure is not identified if the product exited.

[5] In the *At Least One Other Product* model, if there was one or more other items with a price change (in that brand × category × store), the probability of a price change on the new product is 43.50% higher, and the probability the product will be discontinued is 2.06% lower (compared with when no other item has a price change).

[6] If two quarters are tied, we randomly select one of them. The results remain similar if we just omit these items. To ensure we can observe price changes each quarter, we exclude brand × category × store combinations that do not have at least five quarters of sales. The results also survive omitting this requirement.

[7] We also compared the stability of annual price change cycles across different items within the same brand × category. We randomly selected 70% of the items in each brand × category and used these items to identify the anniversary of price changes. We then use the remaining 30% of items as a holdout sample. In the holdout sample, an average of 56.6% (s.e., 0.20%) of items have price changes in anniversary quarters, compared with just 31.7% (s.e., 0.17%) of items in nonanniversary quarters.

[8] For example, if a brand × category × store typically has annual price changes between the third calendar quarter (July–September) and the fourth calendar quarter (October–December) and the new product was introduced in June, then we label the timing as coinciding for this new item (in this store). In contrast, if the new item was introduced in January, we would label the timing as not coinciding.

[9] Reassuringly, the results remain qualitatively similar if we relax any of these filters. For example, preliminary analyses found virtually no differences if we selected a random subset of chains, the first store opening of each chain, or all store openings in some random chains.

[10] We also repeated the analysis when excluding the focal store. As we might expect, this modification has very little impact on the findings.

References

Ailawadi KL, Harlam BA (2009) Retailer promotion pass-through: A measure, its magnitude, and its determinants. *Marketing Sci.* 28(4):782–791.

Anderson ET, Simester DI (2003) Effects of $9 price endings on retail sales: Evidence from field experiments. *Quant. Marketing Econom.* 1(1):93–110.

Anderson E, Jaimovich N, Simester D (2015) Price stickiness: Empirical evidence of the menu cost channel. *Rev. Econom. Statist.* 97(4):813–826.

Anderson E, Malin BA, Nakamura E, Simester D, Steinsson J (2017) Informational rigidities and the stickiness of temporary sales. *J. Monetary Econom.* 90:64–83.

Aparicio D, Rigobon R (2020) Quantum prices. NBER Working Paper No. 26646, National Bureau of Economic Research, Cambridge, MA.

Aparicio D, Metzman Z, Rigobon R (2021) The pricing strategies of online grocery retailers. NBER Working Paper No. 28639, National Bureau of Economic Research, Cambridge, MA.

Bergen M, Levy D, Ray S, Rubin PH, Zeliger B (2008) When little things mean a lot: On the inefficiency of item-pricing laws. *J. Law Econom.* 51(2):209–250.

Blattberg RC, Neslin SA (1990) *Sales Promotion, Concepts, Methods and Strategies* (Prentice-Hall, Englewood Cliffs, NJ).

Blinder AS, Canetti ERD, Lebow DE, Rudd JB (1998) *Asking About Prices: A New Approach to Understanding Price Stickiness* (Russell Sage Foundation, New York).

Bronnenberg BJ, Kruger MW, Mela CF (2008) Database paper: The IRI marketing data set. *Marketing Sci.* 27(4):745–748.

Caro F, Gallien J (2007) Dynamic assortment with demand learning for seasonal consumer goods. *Management Sci.* 53(2):276–292.

Cecchetti SG (1986) The frequency of price adjustment: A study of the newsstand prices of magazines. *J. Econometrics* 31:255–274.

DellaVigna S, Gentzkow M (2019) Uniform pricing in US retail chains. *Quart. J. Econom.* 134(4):2011–2084.

Doraszelski U, Lewis G, Pakes A (2018) Just starting out: Learning and equilibrium in a new market. *Amer. Econom. Rev.* 108(3):565–615.

Dutta S, Bergen M, Levy D, Venable R (1999) Menu costs, posted prices, and multiproduct retailers. *J. Money Credit Banking* 31(4):683–703.

Eichenbaum M, Jaimovich N, Rebelo S (2011) Reference prices, costs, and nominal rigidities. *Amer. Econom. Rev.* 101(1):234–262.

Ellickson PB, Misra S (2008) Supermarket pricing strategies. *Marketing Sci.* 27(5):811–828.

Hitsch GJ (2006) An empirical model of optimal dynamic product launch and exit under demand uncertainty. *Marketing Sci.* 25(1):25–50.

Hitsch GJ, Hortacsu A, Lin X (2021) Prices and promotions in US retail markets: Evidence from big data. *Quant. Marketing Econom.* 19(3):289–368.

Horrace WC, Oaxaca RL (2006) Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Econom. Lett.* 90(3):321–327.

Huang Y, Ellickson PB, Lovett MJ (2022) Learning to set prices. *J. Marketing Res.* 59(2):411–434.

Hwang M, Thomadsen R (2015) How point-of-sale marketing mix impacts national-brand purchase shares. *Management Sci.* 62(2):571–590.

Hwang M, Bronnenberg BJ, Thomadsen R (2010) An empirical analysis of assortment similarities across US supermarkets. *Marketing Sci.* 29(5):858–879.

Kashyap A (1995) Sticky prices: New evidence from retail catalogs. *Quart. J. Econom.* 110(1):245–274.

Knotek ES (2008) Convenient prices, currency and nominal rigidity: Theory with evidence from newspaper prices. *J. Monetary Econom.* 55:1303–1316.

Knotek ES (2011) Convenient prices and price rigidity: Cross-sectional evidence. *Rev. Econom. Statist.* 93(3):1076–1086.

Kruger M, Pagni D (2009) *IRI Academic Data Set Description, Version 1.403* (Information Resources Inc., Chicago).

Levy D, Bergen M, Dutta S, Venable R (1997) The magnitude of menu costs: Direct evidence from large US supermarket chains. *Quart. J. Econom.* 112(3):791–824.

Levy D, Dutta S, Bergen M, Venable R (1998) Price adjustment at multiproduct retailers. *Managerial Decision Econom.* 19(2):81–120.

Levy D, Snir A, Gotler A, Chen H (2020) Not all price endings are created equal: Price points and asymmetric price rigidity. *J. Monetary Econom.* 110(April):33–49.

Levy D, Chen H, Muller G, Dutta S, Bergen M (2010) Holiday price rigidity and cost of price adjustment. *Economica* 77(305):172–198.

Levy D, Lee D, Chen H, Kauffman RJ, Bergen M (2011) Price points and price rigidity. *Rev. Econom. Statist.* 93(4):1417–1431.

McShane BB, Chen C, Anderson ET, Simester DI (2016) Decision stages and asymmetries in regular retail price pass-through. *Marketing Sci.* 35(4):619–639.

Meza S, Sudhir K (2006) Pass-through timing. *Quant. Marketing Econom.* 4(4):351–382.

Nagle TT (1987) *The Strategy and Tactics of Pricing: A Guide to Profitable Decision Making* (Prentice-Hall, Englewood Cliffs, NJ).

Nakamura E, Steinsson J (2008) Five facts about prices: A reevaluation of menu cost models. *Quart. J. Econom.* 123(4):1415–1464.

Nakamura E, Zerom D (2010) Accounting for incomplete pass-through. *Rev. Econom. Stud.* 77(3):1192–1230.

Nijs V, Misra K, Anderson ET, Hansen K, Krishnamurthi L (2010) Channel pass-through of trade promotions. *Marketing Sci.* 29(2):250–267.

Pashigian BP (1988) Demand uncertainty and sales: A study of fashion and markdown pricing. *Amer. Econom. Rev.* 78(5):936–953.

Pashigian BP, Bowen B (1991) Why are products sold on sale?: Explanations of pricing regularities. *Quart. J. Econom.* 106(4):1015–1038.

Ray S, Haipeng AC, Bergen ME, Levy D (2006) Asymmetric wholesale pricing: Theory and evidence. *Marketing Sci.* 25(2):131–154.

Rudolph HJ (1954) Pricing for today's market. *Printers' Ink* 247(May):22–24.

Schindler RM, Kibarian T (1996) Increased consumer sales response through use of 99-ending prices. *J. Retailing* 72(2):187–199.

Schindler RM, Kirby PN (1997) Patterns of rightmost digits used in advertised prices: Implications for nine-ending effects. *J. Consumer Res.* 24(2):192–201.

Slade ME (1998) Optimal pricing with costly adjustment: Evidence from retail-grocery prices. *Rev. Econom. Stud.* 65:331–359.

Stiving M, Winer RS (1997) An empirical analysis of price endings with scanner data. *J. Consumer Res.* 24(June):57–67.

Zbaracki M, Ritson M, Levy D, Dutta S, Bergen M (2004) Managerial and customer costs of price adjustment: Direct evidence from industrial markets. *Rev. Econom. Statist.* 86(2):514–533.