Using Diversion Ratios as a Measure of Brand Performance for Product Line Decisions *

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Abstract

Understanding the impact of product removal on brand performance is critical for making informed product line and assortment decisions. This study employs the non-parametric method of product diversion ratios to empirically investigate the effects of product removal in the grocery retail context. Using IRI store-level data in the peanut butter category from 2001-2011, we analyze roughly 50,000 product removal events to measure the impact on the removed product's own brand category share. Our findings reveal significant variations in diversion ratios and changes in total brand revenue, highlighting the nuanced effects of product removal on brand performance. By leveraging diversion ratios, we provide a practical and intuitive measure that utilizes aggregate sales data to offer insights into brand performance without the need for complex individual-level data. This approach not only captures the immediate shifts in consumer behavior following a product removal but also helps brands and retailers understand the competitive landscape and make more strategic product line and shelf-space management decisions. Our results offer actionable guidance on optimizing product assortments and enhancing brand performance across different retail environments.

Keywords: Product removal, Brand loyalty, Retailing, Product line management, Diversion ratios

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1 Introduction

Permanent product removal is a phenomenon that is an integral part of the dynamic retail landscape. This permanent removal of products from store shelves can be driven by various factors, including logistical constraints and shocks (Kapadia, 2020; Zimmerman, 2022; Hernandez, 2023), cost optimization, and strategic product line decisions by brands or retailers (Kline, 2024). NielsenIQ highlights that the consumer packaged goods market is very dynamic, with an average of 30,000 new products launched each year. This high rate of new product introductions inherently implies a significant level of product delisting and turnover as retailers make room for new items (NielsenIQ, 2019). This high product turnover rate is reflective of the dynamic nature of consumer goods markets. Similarly, McKinsey (2023)'s report on the grocery industry also indicates frequent product turnovers.

Product removals are economically important and could lead to significant shifts in market dynamics, affecting consumer choices and brand performance. For example, if a grocery store manager decides to stop carrying a specific product like 28 ounce Jif Extra Crunchy peanut butter, consumers will likely respond in different ways. Some consumers who used to buy that product might switch to buying other products from Jif, others might switch to buying products from competing brands, and some might even choose to stop being peanut butter at that store altogether. Overall, the product removal will affect market shares for both Jif and its direct competitors. From the perspective of the brand and the grocery store manager, understanding and quantifying these consumer responses is important for evaluting the success of the manager's decision to remove the product from store shelves.

Evaluating the final effect of product removal is crucial for several reasons, especially in an era where consumers have a plethora of choices, and shelf space is a premium commodity (Neiman and Vavra, 2023). Firstly, it helps brands and retailers make informed product assortment decisions. By understanding how the removal of a product impacts overall brand performance, firms can better manage their portfolios. Secondly, it provides insights into competitive structures and substitution patterns. When their preferred product is removed, consumers are forced to break their habits and to switch to alternative options, thereby revealing their true preferences and the competitive relationships between brands. Finally, product removal offers a novel context and another perspective to measure brand loyalty using aggregate data, providing a valuable and low-data-cost tool for marketers.

In this research, we demonstrate an under-utilized method in marketing to achieve these objectives using store-level aggregate sales data. Our approach is based on analyzing consumer responses after products are permanently removed from store shelves, either because the manufacturer has stopped making the product or because the retailer is choosing to no longer carry it. From the consumers' perspective, this product removal creates a shock to their choice set, disrupts their routine, and forces them to make a choice among an updated set of options. We quantify consumers' subsequent purchase behavior using the nonparametric method of diversion ratios from industrial organization, which summarize how brands' shares were affected by the product removal (Conlon and Mortimer, 2022). If a brand's share remains stable despite the product removal, then this implies that the affected consumers have relatively high loyalty towards the brand — even after their preferred product was no longer available, they still purchased from the same brand. On the other hand, if a brand's share drops substantially after a product is removed from shelves, this implies that consumers have low brand loyalty because they switched to one of the competitors. By analyzing how demand shifts after a product removal, we can identify which products are crucial for brands and are critical to retain in the assortment. Conversely, other products may be candidates for removal if their absence does not significantly impact overall brand performance.

Diversion ratios offer several advantages to study the effect of product removals and to infer brand loyalty from consumer responses. They are intuitive to understand and interpret, making them accessible to managers. Second, they are nonparametric and do not require strong assumptions about consumer demand, consumer utility, or statistical distributions of parameter values. Third, they do not require special data collection; instead, they can be estimated using aggregate store-level sales data that retailers and brands typically already have access to.

To demonstrate our proposed approach, we estimate diversion ratios after product removals in the peanut butter category. This category serves as a good exemplar because product removal events are regular occurrences, products are purchased relatively often, and consumers have long-standing preferences. Furthermore, as with many other consumer packaged goods categories, it is a competitive and stable category with a large number of brands and products that are available for the consumer to choose from. In theory, this large product assortment is helpful for consumers because it means they can buy peanut butter products that are closely aligned with their preferences, but it also potentially causes production inefficiencies for brands and takes up valuable shelf space for the retailer (Neiman and Vavra, 2023). In these types of settings, a better understanding of consumers' responses can help brands and retailers make better product line management and stocking decisions.

Our main metric of interest is the own-brand diversion ratio, which measures the extent to which a product's demand is retained by the focal brand after the product is removed from a store. After analyzing roughly 50,000 product removal events in the peanut butter category using IRI store-level data from 2001 to 2011, we find that the diversion ratio changes over time for brands and varies between brands. To understand this heterogeneity, we use regression analysis to examine how the diversion ratios vary across different kinds of products and stores. This analysis provides several insights.

First, there is an inverted U-shaped effect of brands' shelf space on the diversion ratio. Shelf space, which serves as a proxy for a brand's assortment size and visibility, shows that brands with moderate shelf space retain the highest proportion of demand after a product removal. In contrast, brands with either very small or very large shelf space experience lower diversion ratios. Smaller brands may lack the visibility needed to drive intra-brand substitution, while overly dominant brands might oversaturate the market, reducing the perceived uniqueness of their offerings and encouraging consumers to switch to competitors when a product is removed.

Second, there is a U-shaped effect of focal products' market share on the diversion ratio. Products with very high or very low market shares tend to yield higher diversion ratios upon removal, whereas medium-market-share products exhibit the lowest retention rates. For high-market-share products, strong brand equity and consumer loyalty drive substitution within the brand, even in the absence of a preferred product. On the other hand, low-market-share products appear to cater to niche consumer preferences, where loyalty to the brand persists despite their lower popularity. Medium-market-share products, however, may lack the distinguishing characteristics that foster strong substitution patterns, making them more susceptible to share losses.

Lastly, diversion ratios are influenced by the retail environment, including the number of competing brands and store size. Larger stores and those offering a broader assortment of competing brands tend to exhibit lower diversion ratios, suggesting that consumers in these settings have greater access to alternatives and are less dependent on any single brand. This underscores the need for brands and retailers to tailor product assortment decisions to the specific retail context. For instance, in smaller stores with limited competition, retaining niche or high-market-share products may better support brand loyalty, while in larger, more competitive environments, brands may need to emphasize products with distinct attributes to stand out among alternatives.

Our approach aligns with the empirics-first methodology outlined by Golder et al. (2023), which emphasizes deriving relevant knowledge directly from data rather than imposing a priori theoretical frameworks. This approach is particularly suitable for analyzing the effects of product removals because of the inherent complexity of retail systems and the multifaceted decisions made by brands and retailers that are often unobservable.

For instance, a retailer might remove a product due to supply chain constraints, low profitability, conflict with the manufacturer, or as part of a broader change in their product assortment strategy. These actions can influence the observed diversion ratio but may stem from motivations unrelated to consumer preferences, complicating theoretical predictions. Similarly, there can be several plausible mechanisms may simultaneously influence consumer responses to that removal event. If consumers choose to buy to another product within the same brand, this might be because consumers have strong brand loyalty, because the removed product had low distinctiveness, or because the removal reduced choice overload. Conversely, if consumer switch to another brand, this might be because the removed product served a niche market with unique attributes, because competitors seized the opportunity to promote similar products, or because the product removal disrupted the brand's perceived assortment completeness.

Given these complexities, our approach deliberately avoids predefining conceptual models. Instead, we focus on empirical analysis to monitor and quantify brand performance using readily available, low-cost aggregate data. By doing so, we empower brands and retailers to respond to real-world outcomes rather than relying on potentially misleading theoretical assumptions.

Our research contributes to several streams of literature, including brand loyalty, consumer behavior in response to product unavailability, product line management, and the use of diversion ratios in marketing. By synthesizing these diverse literatures, we provide a novel perspective on the effects of product removal and introduce a new method for measuring brand loyalty using aggregate data. These findings have important implications for both brands and retailers, helping them to navigate the dynamic and competitive consumer goods markets.

Our use of diversion ratios offers a cost-effective and practical alternative to traditional brand loyalty and brand performance monitoring methods. Unlike survey-based studies, which can incur high costs and biases, diversion ratios utilize publicly available store-level data, enabling retailers and brands to gain valuable insights into consumer loyalty patterns at a fraction of the data collection cost. Unlike structural econometric models, which often rely on individual-level data and/or involve assumptions about consumer preferences and demand functions, our nonparametric approach is straightforward to implement and flexible for various retail settings. By bypassing the need for consumer utility estimations, our diversion ratio-based method reduces data requirements, assumptions, and analytical complexity. Additionally, as the diversion ratio is calculated at the store-level, the tool provides brands with localized insights on consumer loyalty, reflecting regional variations in brand performance and allowing for nuanced, store-specific product assortment decisions.

In the data we examine, each product removal event occurred because either a brand or a retailer chose to remove that product from shelves. Our reliance on this observational data means that we cannot use our estimated diversion ratios to make predictions for market shares or diversion ratios for future (hypothetical) product removal events. In order to generate those values, a brand would need to conduct a randomized experiment wherein the same product is systematically removed in some stores but left in others to create exogenous variation — while this approach would avoid endogeneity concerns, we also believe that it is not realistic for most brands or retailers.

The goal of this research and our diversion ratio method is to provide a descriptive tool that can give brands and retailers feedback about how successful their product removals have been, both in isolation and relative to the competition. There are some product removal events that consumers respond positively vs. negatively to, and the key decision makers in this process (brands and retailers) benefit from being able to monitor these outcomes and measure these consumers responses in a coherent way.

2 Background and literature review

This research sits at the intersection of four primary topics: brand loyalty, consumer responses to product unavailability, product line management and product assortment, and diversion ratios. Below, we expand on the literature in each of these areas to establish the theoretical foundation for our study.

2.1 Brand loyalty

Brand loyalty is a central component in our phenomenon of interest, that is, brand performance after product removal. Brand loyalty has been extensively researched in marketing literature, focusing on its definition, antecedents, and measurement (Mellens, Dekimpe, and Steenkamp, 1996; Brady et al., 2008; Watson et al., 2015). A widely used definition by Watson et al. (2015) describes brand loyalty as "a deeply held commitment to rebuy or repatronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior".

Jacoby and Chestnut (1978) defines brand loyalty as a concept that needs to satisfy six conditions: "The (a) biased, (b) behavioral response, (c) expressed over time, (d) by some decision-making units, (e) with respect to one or more alternative brands out of a set of such brands, and (f) is a function of psychological (decision-making evaluative) processes."

Despite this thorough theoretical framework for brand loyalty, measuring it accurately in practice has proven challenging, especially with secondary sales data. Traditional approaches typically combine behavioral measures, such as repeat purchase rates and share of category requirements, with attitudinal measures derived from surveys assessing consumer perceptions and preferences (Jacoby and Chestnut, 1978; Mellens, Dekimpe, and Steenkamp, 1996). Each of these has limitations: behavioral measures risk conflating inertia with loyalty, as consumers may repurchase a brand out of convenience rather than preference. Attitudinal measures, while capturing psychological commitment, are often time-consuming, resource-intensive, and difficult to validate against actual purchasing behavior.

We tackle these empirical challenges of measuring brand loyalty in this work, and each of Jacoby and Chestnut (1978)'s requirements naturally aligns with our research setting, where brand loyalty in response to product removal can be observed and quantified using diversion ratios. As listed below:

Biased response: Loyalty is inherently biased, meaning consumers exhibit a preference for a specific brand over alternatives. In our context, the diversion ratio serves as a measure of this bias by quantifying the extent to which consumers of a removed product remain within the same brand rather than switching to competitors. A high diversion ratio reflects a strong brand bias, indicating that consumers are willing to substitute to products within the same brand rather than seeking alternatives outside the brand.

Behavioral response: Loyalty is reflected in observable behaviors, such as the act of repurchasing or choosing the brand over time. The response to product removal provides a unique setting for capturing behavioral loyalty. By analyzing how a brand's market share changes when a product is removed, we can observe whether consumers' behaviors reflect genuine loyalty (staying within the brand) or convenience-driven, habitual purchasing that shifts to competitors.

Temporal consistency: Loyalty is expressed over time, reflecting enduring consumer commitment rather than short-term choices. Our approach has a built-in temporal component – it measures brand performance before and after removal.

Decision-making units: Brand loyalty is specific to certain decision-making units (such as households or individual consumers). While our nonparametric method does not capture individual decision-makers directly, the aggregate data at the store level effectively represents collective decision-making behaviors within localized consumer groups. This approach provides insights into how communities or regions respond to brand changes.

Competitive set: Loyalty is evaluated concerning a specific set of alternative brands. In our study, when a product is removed, the consumer is forced to make a decision when looking at the shelf of remaining products. The diversion ratio explicitly considers this competitive set by quantifying the impact of a product's removal on both intra-brand and inter-brand substitution patterns.

Psychological process: Lastly, Jacoby and Chestnut (1978) emphasize that loyalty is influenced by psychological factors, reflecting a consumer's attachment and evaluative processes. Although our nonparametric approach does not directly measure psychological commitment, high diversion ratios indirectly capture the effect of brand attachment by indicating consumers' resistance to switching away from a preferred brand.

There is also a stream of papers that uses economic theory, econometric tools, and structural models to disentangle the role of switching costs, state dependence, and other explanations for repeat purchase behavior (e.g., Roy, Chintagunta, and Haldar, 1996; Dubé, Hitsch, and Rossi, 2010; Kong, Dubé, and Daljord, 2022). This part of the literature focuses on a different issue than we do, because our goal is to provide a nonparametric summary of brand loyalty rather than to disentangle these different underlying processes.

That said, structural models can also be used to assess brand loyalty. A typical setup for structural models require detailed, individual-level transaction data, such as household panel data or loyalty card data. They also require assumptions about the utility function structure, consumers' rationality and information set, and the substitutability or complementarity between products. Computationally, these approaches are more demanding, as they often involve estimating a large number of parameters across different product and consumer attributes and require more complex estimation methods involving likelihoods and/or moment conditions.

Structural modeling approaches could yield a broad array of insights, including price elasticity, marginal willingness-to-pay, and simulated responses to hypothetical market changes. This depth of insight makes them suitable for strategic planning. However, the complexity of structural models may limit interpretability for managers, who may prefer the simpler, actionable insights provided by diversion ratios. Diversion ratios offer a more flexible, scalable alternative for everyday brand performance monitoring across multiple store locations, as they adapt well to store-level decision-making without extensive assumption, data requirements, and calibration.

Our study contributes to this stream by proposing a new method for quantifying brand loyalty using diversion ratios derived from store-level aggregate sales data. This approach leverages the nonparametric nature of diversion ratios to provide a practical and intuitive measure of brand loyalty, overcoming some limitations of traditional measures that require individual-level data and complex modeling (Conlon and Mortimer, 2022). Our research context satisfies all six conditions mentioned above by Jacoby and Chestnut (1978) because we observe consumer behavioral changes in response to product removals in the presence of alternatives.

2.2 Consumer responses to product unavailability

A significant body of literature examines how consumers respond to product unavailability, including product discontinuation and stockouts. Breugelmans, Gijsbrechts, and Campo (2018) provide a recent summary of consumer behavior in response to temporary stockouts, highlighting various coping strategies such as brand switching and purchase delay. Temporary stockouts can be caused by positive demand shocks, whereas our study focuses on permanent product removals, which represent a more deliberate strategic decision by retailers and brands.

Previous studies have investigated the impact of product unavailability on consumer behavior. For example, Sloot, Verhoef, and Franses (2005) examined how brand equity and product characteristics influence consumer reactions to stockouts, finding that consumers with strong brand preferences are less likely to switch brands during stockouts. Similarly, Anderson, Fitzsimons, and Simester (2006) explored how stockouts affect consumer preferences and purchase intentions, suggesting that stockouts can sometimes enhance the desirability of unavailable products (Sloot, Verhoef, and Franses, 2005; Anderson, Fitzsimons, and Simester, 2006).

Our research contributes to this literature by focusing on the long-term effects of permanent product removals, which force consumers to adjust their purchase behavior permanently.

Permanent removals can have different implications compared to temporary stockouts where consumers can wait, as they necessitate a complete reevaluation of consumer choices and loyalty.

There is also a recent set of papers that examine how consumers behave in response to store closures, which represent a more significant shock to the consumers' usual shopping behavior (Raval, Rosenbaum, and Wilson, 2022; Tohidi, Eckles, and Jadbabaie, 2022). In contrast, our paper follows in a literature that addresses issues related to product assortment consolidation (Broniarczyk, Hoyer, and McAlister, 1998), and the closest papers to ours are those which examine shoppers' behavior after products have been removed from shelves (Wiebach and Hildebrandt, 2012; Piris, 2013; Hebblethwaite, Parsons, and Spence, 2017). Within this literature, we are perhaps most close in goals to Zhang and Krishna (2007), which also examines brand performance after product removal. While that paper uses a formal utility-based model of consumer demand using consumer-level data, our study distinguishes itself by employing a non-parametric approach using diversion ratios to analyze the effects of product removals. This method allows us to bypass the need for individual-level data and parametric assumption. This approach offers several advantages: it is more accessible to managers, intuitive to interpret, and more feasible for large-scale application. Additionally, while Zhang and Krishna (2007) focus on the effects of product line reductions using household-level data from a single online retailer, our study captures the broader retail context by analyzing a decade's worth of data from physical grocery stores that vary in store-level characteristics. This allows us to provide insights to retailers as well as brands.

2.3 Product line management and product assortment

Product line management and product assortment decisions are important for optimizing retail performance. This literature emphasizes the trade-offs between offering a wide variety of products to meet diverse consumer preferences and the operational efficiencies gained from reducing product complexity (Dreze, Hoch, and Purk, 1994; Chiang and Wilcox, 1997;

Boatwright and Nunes, 2001; Gourville and Soman, 2005; Sloot, Fok, and Verhoef, 2006; Berger, Draganska, and Simonson, 2007; Briesch, Chintagunta, and Fox, 2009; Hwang, Bronnenberg, and Thomadsen, 2010; Mani, Thomas, and Bansal, 2022; Sethuraman, Gázquez-Abad, and Martínez-López, 2022). For example, Dreze, Hoch, and Purk (1994) studied the effects of shelf space allocation on product sales, demonstrating that optimal shelf management can significantly influence consumer choice and category performance. Broniarczyk, Hoyer, and McAlister (1998) found that consumers perceive assortments with fewer items as less attractive, which can negatively impact sales. However, they also found that if the remaining products are well-chosen and cover the key needs of consumers, the negative impact can be mitigated.

More recent research by Neiman and Vavra (2023) highlights the rise of niche consumption and its implications for product assortment decisions. They argue that with the increasing availability of niche products online, consumers are more likely to seek out specific items that cater to their unique preferences. This shift towards niche consumption requires retailers to carefully balance variety and efficiency to meet changing consumer demands.

Our study contributes to this literature by utilizing diversion ratios as a novel yet intuitive approach for assessing the impact of product assortment decisions. Given the heterogeneity of stores and brands of our study's context, this can help brands and retailers of different characteristics make more informed decisions about which products to retain or remove from their assortments, balancing the need for variety with the benefits of efficiency.

2.4 Diversion ratios

The concept of diversion ratios originates from economics and its industrial organization subfield, where it has primarily been used to analyze the effects of mergers and competition. Diversion ratios measure the proportion of demand that shifts from a removed product to other products within the same category. This metric provides valuable insights into substitution patterns and competitive dynamics (Farrell and Shapiro, 2010; Conlon and

Mortimer, 2022).

Diversion ratios have traditionally been used in merger analysis to evaluate the competitive effects of combining firms. For example, Farrell and Shapiro (2010) discussed how diversion ratios can help antitrust authorities assess the potential for anti-competitive behavior in horizontal mergers. They argue that high diversion ratios between merging firms suggest that the merger could significantly reduce competition and harm consumers. Conlon and Mortimer (2022) extended this application to the analysis of consumer behavior, demonstrating how diversion ratios can be used to predict market outcomes in various contexts. They found that diversion ratios are useful for understanding how consumers substitute between products, providing insights into the competitive landscape and the strength of consumer preferences.

To the best of our knowledge, our study is the first to apply diversion ratios to the context of product removal in retail settings. This approach offers several advantages, including simplicity, nonparametric estimation, and the use of readily available aggregate sales data. Diversion ratios allow us to quantify the impact of product removal on brand loyalty and category dynamics without requiring detailed individual-level data.

3 Empirical analysis

3.1 Data

We use IRI sales data from 2001 – 2011 as our measure of consumer sales. This data includes weekly sales at the product (universal product code; hereafter UPC) level for each store. For a full description of the data set, see Bronnenberg, Kruger, and Mela (2008).

To focus our analysis, we narrow the data to the peanut butter category. This category offers several advantages for examining brand loyalty and substitution behavior. Peanut butter is highly competitive, dominated by several well-established brands like Jif, Skippy, and Peter Pan, each with a broad product range. The category is also stable and less

Variable	Value
Years	2001 – 2011
Num. peanut butter brands in the IRI data	63
Num. peanut butter brands with at least one product removal	42
Num. stores with at least one peanut butter product removal	2563
Num. peanut butter product removal events	49,879

Table 1: Summary of the product removal data

influenced by rapid innovation, making it easier to isolate consumer responses to product removal from other factors such as new product introductions. Furthermore, peanut butter is frequently purchased, which provides sufficient data points to observe meaningful patterns in consumer behavior.

We further refine our data by examining permanent product removal events within this period. We define a permanent removal as an instance where a UPC disappeared from the store's sales records and did not reappear at any later date.[1] To ensure that we capture the effects of partial product removal rather than full brand exit, we exclude events where an entire brand was removed from a store's shelves, focusing instead on cases where at least one other product from the same brand remained available.

Table 1 provides a summary of our data that illustrates the scope of our analysis. In total, our dataset includes nearly 50,000 product removal events across 2,563 stores and 63 brands. Of these brands, 42 experienced at least one product removal during the analysis period. For each of these product removal events, we can calculate the diversion ratio using sales data from before and after the event occurred.

In Figures 1 and 2, we show the number of product removal events by year and by brand. Figure 1 shows a spike in the number of product removal events in 2002 and 2003, but in the remaining years the number of events usually ranges from 2,500 – 5000. Meanwhile,

[1] Our original data also included a subsequent year of sales data (in 2012). We do not use any of the 2012 product removal events in our data, because we cannot be sure whether those products returned to shelves in 2013. Instead, we use the 2012 data solely to ensure that products removed during the 2001 – 2011 did not return to shelves at any point in 2012. Therefore, our precise definition of "permanent product removal" is that the product was removed from shelves from some point during 2001 – 2011 and it did not return to shelves by the end of 2012.

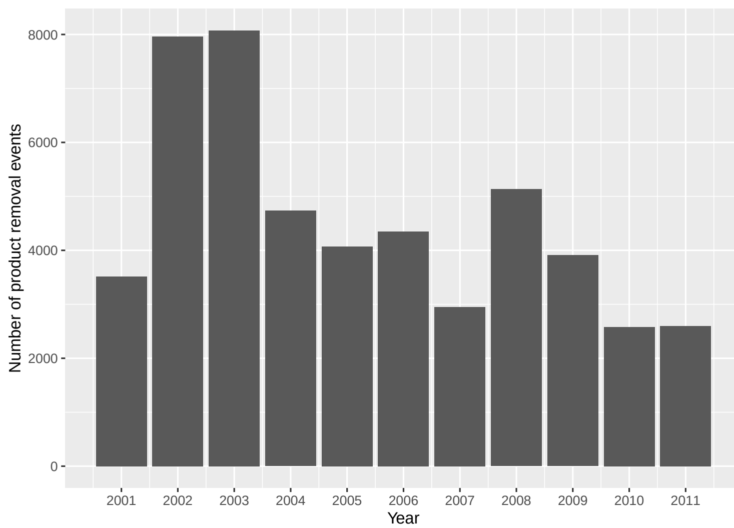


Figure 1: Number of product removal events by year

Figure 2 shows that product removal events are more frequent among the larger brands like Jif, Peter Pan, and Skippy, in large part because these brands have larger product lines and more products on store shelves to begin with.

3.2 Estimating diversion ratios

Our key metric for brand loyalty is the own-brand diversion ratio, which measures how much demand is retained by the brand after a product removal event. We begin by denoting q_j as the quantity sold by brand j, and then by defining brands' market share at the store level as their sales quantity divided by category sales.[2] We can also define similar quantities and market shares at the product level. For the sake of simplicity, we omit subscripts for week, store, and product category. Therefore, for brand j or for product i, the market shares are:

$$\text{Brand level market share: } s_j = \frac{q_j}{q_j + \sum_{k \neq j} q_k} \tag{1}$$

$$\text{Product level market share: } s_i = \frac{q_i}{q_i + \sum_{m \neq i} q_m} \tag{2}$$

[2]To account for differences in package sizes, we use volume-weighted sales quantities q rather than simply using the number of items sold.

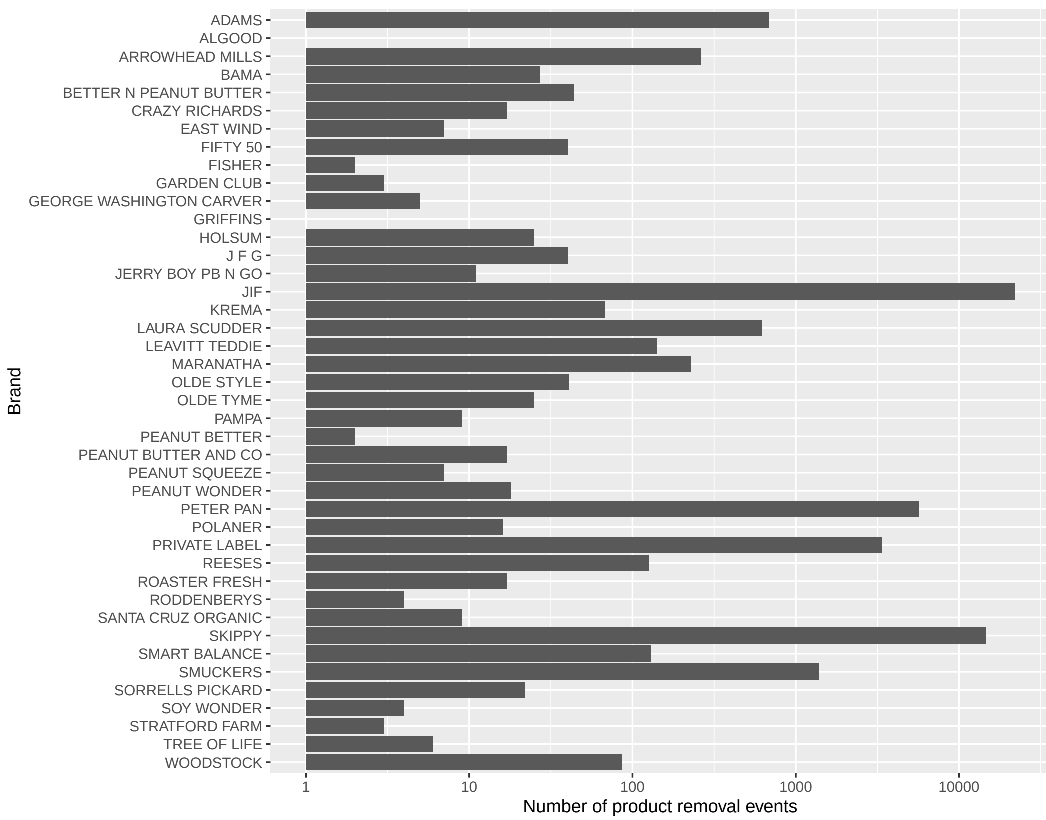


Figure 2: Number of product removal events by brand. The horizontal axis is on a logarithmic scale.

The next step is to separately measure three market shares for each product removal event r:

1. The product-level market share (before the product removal event) for the product that was removed. We label this term as s_{ir}^{pre}.

2. The brand-level market share (before the product removal event) for the brand whose product was removed. We label this term as s_{jr}^{pre}.

3. The brand-level market share (after the product removal event) for the brand whose product was removed. We label this term as s_{jr}^{post}.

All three of these market shares need to be estimated on a predetermined window of time before and after the product removal event. We calculate s_{ir}^{pre} and s_{jr}^{pre} based on data for the 3 weeks before the product removal, and we calculate s_{jr}^{post} based on data from 2-5 weeks after the removal.[3] Given these market shares, the own-brand diversion ratio D_{jr} can be defined as the relative change in the brand's market share after the product removal event, compared to the market share of the removed product itself:

$$
\begin{aligned}
D_{jr} &= \frac{\text{brand market share after removal event} - \text{brand market share before removal event}}{\text{product market share before removal event}} \\
&= \frac{s_{jr}^{\text{post}} - s_{jr}^{\text{pre}}}{s_{ir}^{\text{pre}}}
\end{aligned} \tag{3}
$$

Figure 3 provides a summary of different ranges of diversion ratio values. From an interpretation standpoint, the two key inflection points in the diversion ratio number line are -1 and 0. We summarize some of the key ranges as follows:

If the diversion ratio is below -1: after the product removal event, the brand's market share declined by *more* than the removed product was responsible for. This implies that removing the product was especially damaging to the brand — in addition to losing all the demand from the removed product, the brand also lost additional demand beyond that.

If the diversion ratio is exactly -1: after the product removal event, the brand lost 100% of the market share that the removed product was responsible for, thereby implying that consumers did not substitute to other products sold by that same brand.

If the diversion ratio is between -1 and 0: after the product removal event, the brand lost some market share, but less than the removed product was responsible for. This implies that some of the consumers engaged in intra-brand substitution when their preferred product was removed.

If the diversion ratio is exactly 0: after the product removal event, the brand's market

[3] We choose these windows in order to balance two goals: (1) Using data from as close to the removal event as possible, because that minimizes the possibility of other store-level changes having an effect on the result, and (2) Omitting data from the date of the product removal and the first week afterwards, because those weeks' sales might be affected by consumers behaving as if the product is only temporarily stocked out.

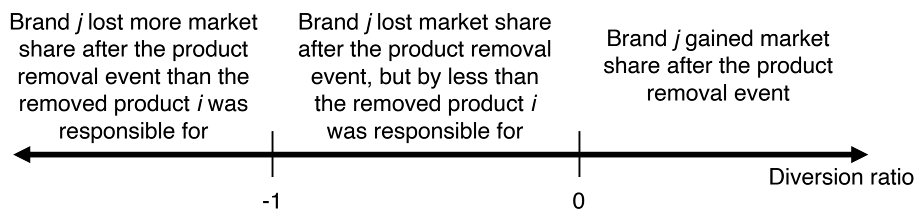


Figure 3: Interpretation of diversion ratio values for a particular brand j and removed product i. If the diversion ratio is -1, then this means that brand j lost exactly 100% of the market share that the removed product i was responsible for. If the diversion ratio is 0, then this means that brand j's market share was unchanged.

share was unchanged. The brand retained all of its demand, thereby implying that all the consumers of the removed product engaged in intra-brand substitution when their preferred product was removed.

If the diversion ratio is above 0: after the product removal event, the brand's market share *increased*. One possible explanation is that consumers were attracted by a less-busy shelf with fewer unique UPCs.

Figure 4 shows a histogram of estimated diversion ratios based on our data, after trimming the top and bottom 10% of values.[4] We find that the typical diversion ratio is positive, with a median of 0.71 and mean of 2.29. This suggests that for the typical product removal event, brands are able to retain demand within their product lines. However, there is a substantial amount of variation across product removal events, with many diversion ratios that are much more strongly positive and others that are negative. The 25th and 75th percentile values are -1.33 and 4.80, respectively. This heterogeneity is a key motivation for our subsequent analysis, which seeks to explain why certain brands or products are more successful in retaining consumers post-removal, while others see a greater shift to competitors.

Although Figure 4 can provide information about the variation in diversion ratios, it is not sufficient for understanding brand performance or differences across at brands. For a first attempt at characterizing brand performance after the product removal, we now show brand level summaries of the diversion ratios in Figure 5. Although the median diversion ratio tends

[4]This trimming process ensures that our graphs and subsequent results are not affected by outliers.

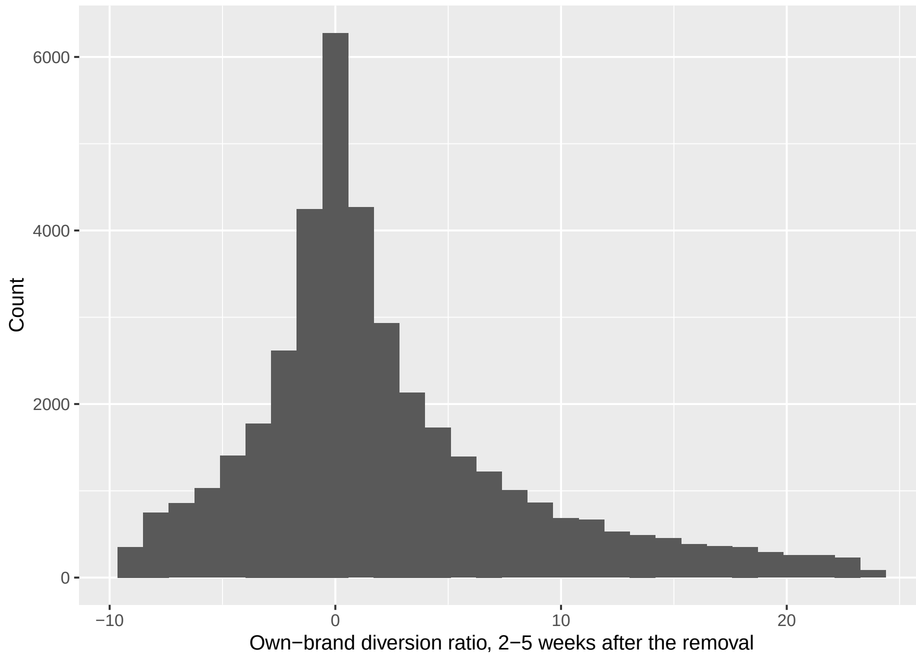


Figure 4: Histogram of diversion ratios. Each observation corresponds to a specific product removal event. The top and bottom 10% of diversion ratio values are trimmed.

to be positive and small for all brands, the diversion ratios can differ substantially in their range. For instance, even brands like Jif and Skippy with a relatively high median diversion ratio have a wide range of values, and many of their product removal events generate large and negative diversion ratios. This variability points to several potential factors influencing retention.

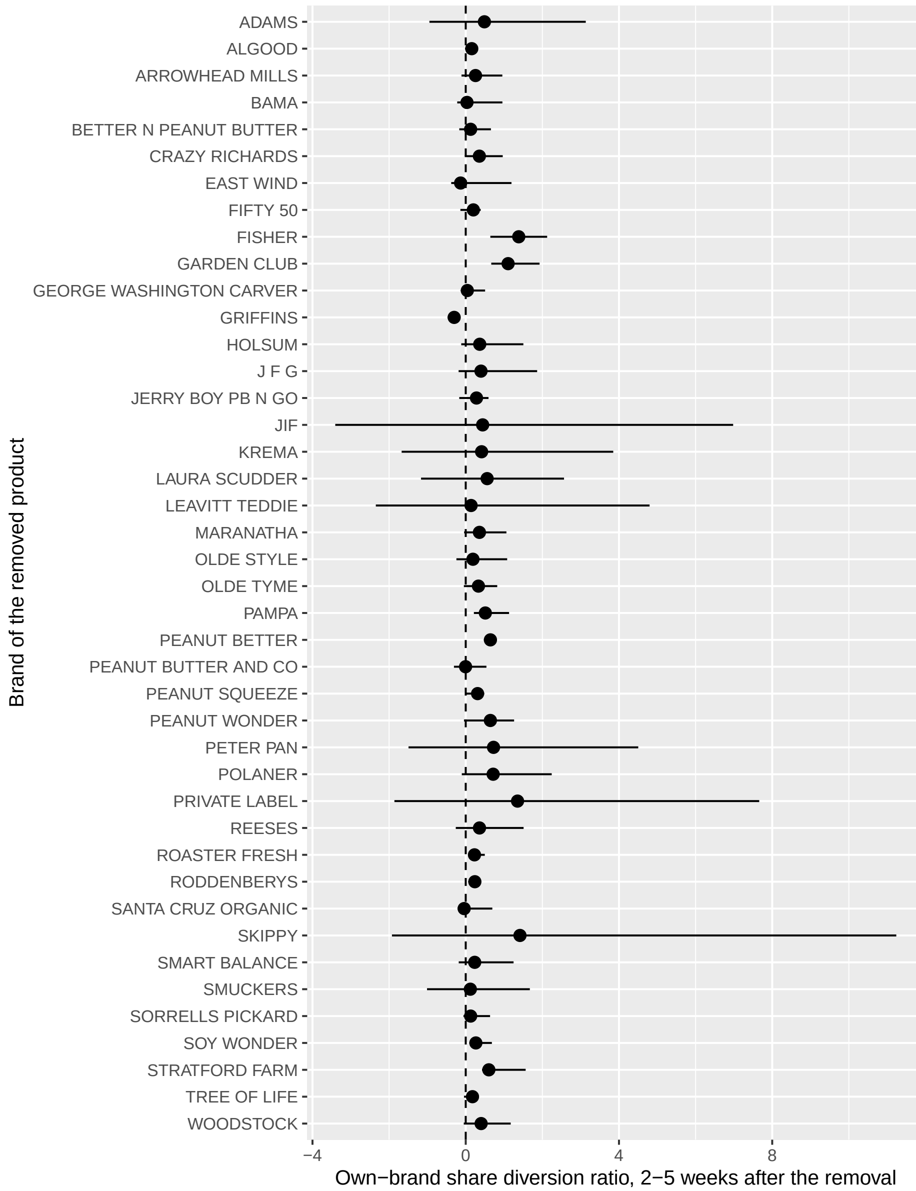


Figure 5: Plot of brands' diversion ratios. Each diversion ratio corresponds to a specific product removal event, and these values are summarized by brand. For each brand, the dot represents the median diversion ratio and the line represents the 25th – 75th percentile values.

One major factor is product portfolio diversity. Large brands like Jif and Skippy tend to offer a variety of products catering to different consumer preferences (e.g., creamy vs. crunchy, reduced fat, and natural options). While this diversity generally supports intra-brand substitution by allowing consumers to find suitable alternatives within the brand, the removal of a unique product within the portfolio may lead to brand switching if its specific attributes are distinctive or hard to replicate; see Ataman, Van Heerde, and Mela (2010) for a broader discussion of this point. This can result in negative diversion ratios.

Another influencing factor is product-specific loyalty. While a high median diversion ratio suggests strong brand loyalty, the presence of significant negative values implies that some consumers are more loyal to specific products than to the brand itself. When a preferred product is removed, consumers with strong product-specific loyalty are more likely to switch to competitors, rather than substitute within the brand, leading to a wider spread in diversion ratios.

Competitive dynamics at the store level can also be a factor. In stores where competitors hold substantial shelf space or have a close substitute available, consumers may be more inclined to switch outside the brand when a product is removed, particularly if competing products offer similar features or price points.

Shelf placement and visibility also contribute to this variability. Products with higher visibility may drive higher retention when a brand's other products are removed. In contrast, less prominent placement can lead to increased brand switching upon product removal. These are the factors that we will explore in subsequent analyses.

3.3 Diversion ratio patterns for larger removal events

One limitation of our diversion ratio formula (equation 3) is that the denominator is the product market share before the removal event (s_{ir}^{pre}). This term is often quite small, which makes the diversion ratio numbers potentially unstable in cases where the removed product has low market share. This would yield more extreme estimated diversion ratios, which would be reflected in the significant heterogeneity observed in figures 4 and 5.

To sidestep this issue, we now narrow our attention to larger removal events, which we define as products that had at least 5% market share prior to the product removal. Figure 6 shows a trimmed histogram of diversion ratios. The median is -0.02 and the mean is 0.02; overall, the diversion ratio values are both lower and less dispersed than the analogous histogram for all product removal events (Figure 4). Similarly, Figure 7 shows brand-level diversion ratios, but only including product removal events that had at least 5% market share. Once again, the diversion ratios are both lower and less dispersed when compared with the analogous figure for all product removal events (Figure 5). From both of these figures, the main takeaway is that when we focus on larger removal events (for products with at least 5% market share), the diversion ratios tend to be closer to zero and are typically negative. Brands lose market share when these kinds of products are removed from store shelves.

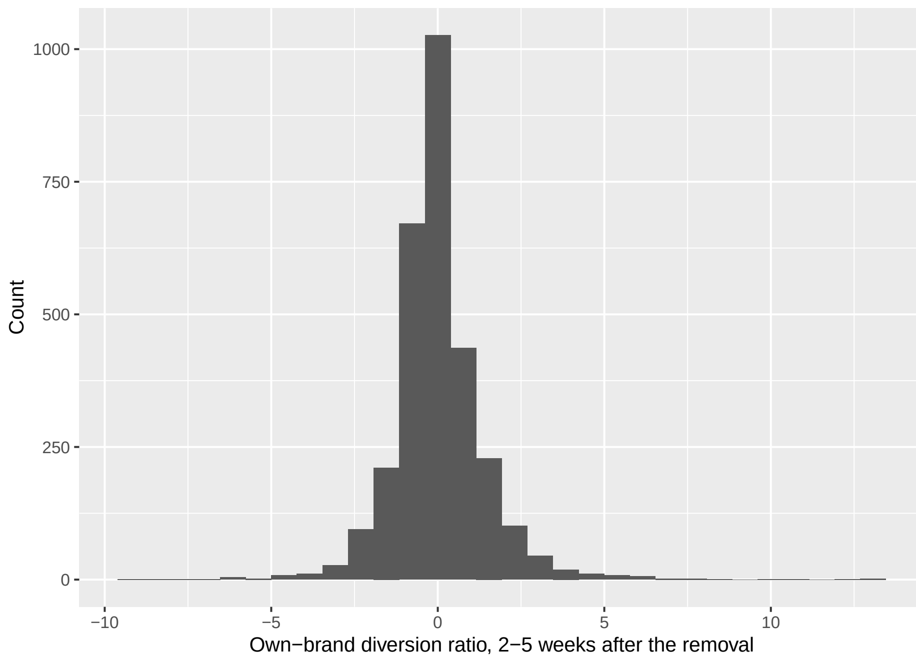


Figure 6: Histogram of diversion ratios. Each observation corresponds to a specific product removal event. The top and bottom 10% of diversion ratio values are trimmed. This graph only includes removal events for products that had at least 5% market share prior to the product removal.

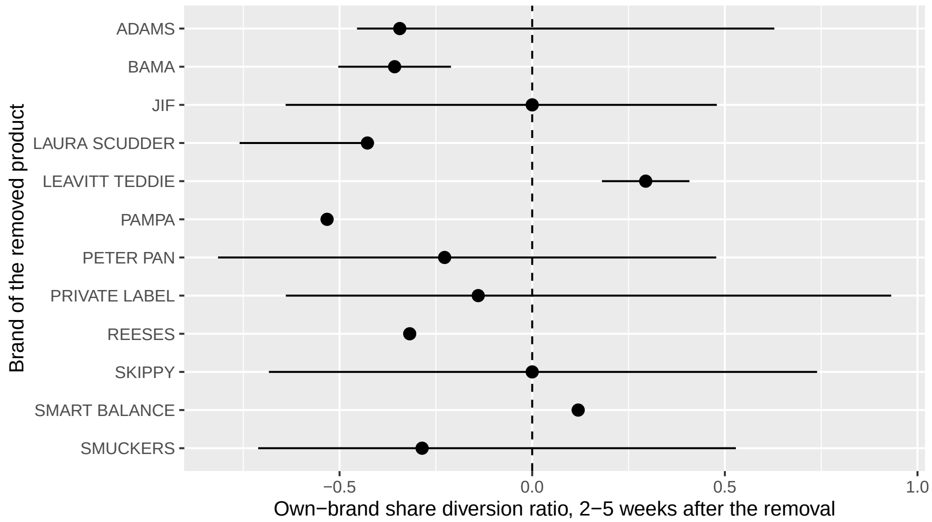


Figure 7: Plot of brands' diversion ratios. Each diversion ratio corresponds to a specific product removal event, and these values are summarized by brand. For each brand, the dot represents the median diversion ratio and the line represents the 25th – 75th percentile values. This graph only includes removal events for products that had at least 5% market share prior to the product removal.

These findings suggest that products with larger market share are integral to sustaining brand retention. When these products are removed, consumers are less inclined to substitute within the brand, likely due to the product's significant role in the brand's appeal. Unlike smaller-market-share products which may be more easily replaced within a brand, high-share products often serve as cornerstones of brand identity, representing key offerings that resonate strongly with consumers. The findings reveal that these high-share products anchor brand loyalty, as their removal appears to disrupt consumer purchasing patterns. It appears that popular products drive the perception of brand value and consistency. When removed, such products leave a gap that other brand items may not adequately fill, causing consumers to seek alternatives from competing brands. Managerially, these analyses suggest that strategic retention of high-share items could mitigate loyalty erosion and enhance brand resilience in response to product-line changes.

The temporal analysis in Figure 8 tracks the average diversion ratios over time, providing insights into how loyalty dynamics evolve within the category. The diversion ratios generally range from -0.2 to 0.2, with a slight dip during 2006–2008, followed by gradual increases in subsequent years. This period of lower diversion ratios could indicate shifts in the competitive landscape, macro economic factors or changes in consumer preferences that could have made it more challenging for brands to retain loyalty. Over time, as economic conditions stabilize, we observe a recovery, with diversion ratios edging towards positive values.

For the three largest brands (Jif, Skippy, and Peter Pan), shown in Figure 9, distinct loyalty trajectories are evident. Jif exhibits a steady increase in diversion ratios, indicating growing consumer loyalty over time. In contrast, Skippy and Peter Pan demonstrate less consistency, with diversion ratios fluctuating more markedly, suggesting that these brands face more variable consumer loyalty. This brand-specific differentiation highlights how diversion ratios can serve as an effective metric for tracking loyalty trends over time, offering valuable insights for strategic brand management.

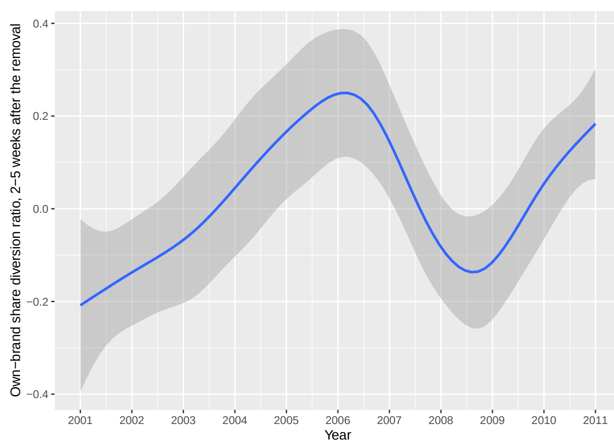
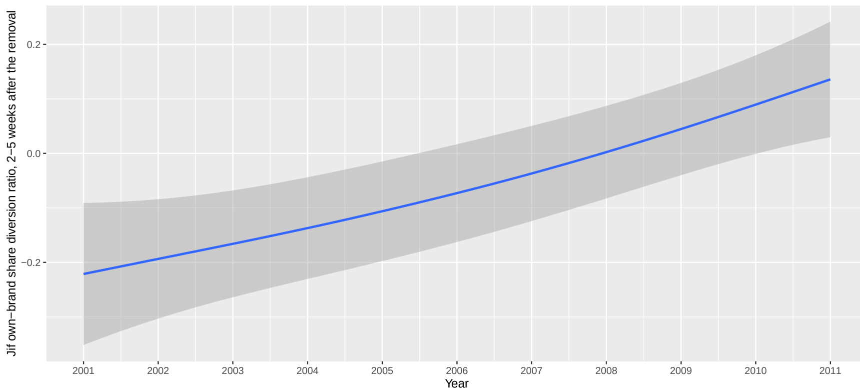


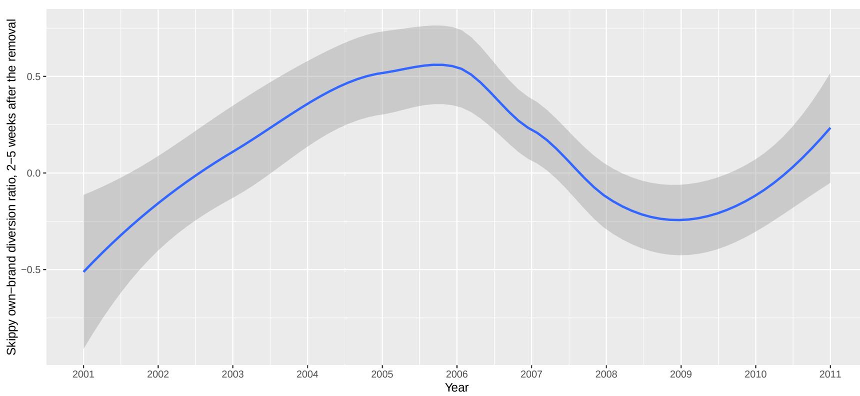
Figure 8: Smoothed line graph of average diversion ratios over time. Each diversion ratio corresponds to a specific product removal event. This graph only includes removal events for products that had at least 5% market share prior to the product removal.

The patterns from these graphs offer observations and implications for long-term brand management:

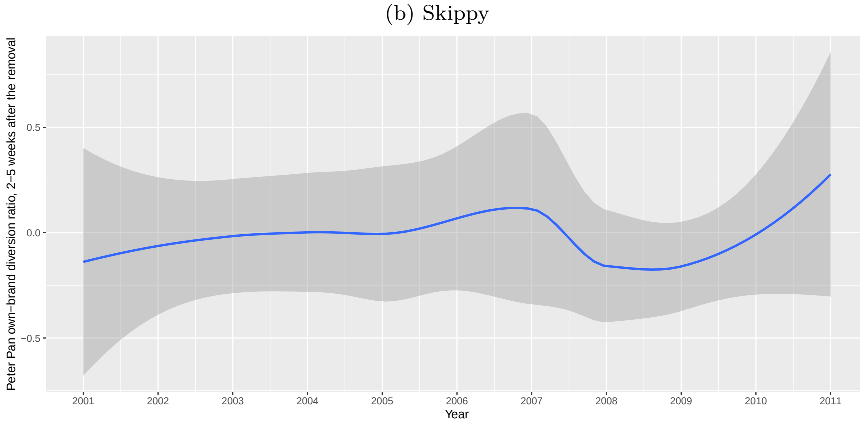
Temporal stability and brand health: The smoothed line graph in Figure 8 demonstrates that diversion ratios remained relatively stable over time, with minor fluctuations. This stability is indicative of consistent consumer loyalty across the category, suggesting a mature market with predictable consumer behaviors. For brand man-



(a) Jif



(b) Skippy



(c) Peter Pan

Figure 9: Smoothed line graph of average diversion ratios over time for the three largest brands. Each diversion ratio corresponds to a specific product removal event. This graph only includes removal events for products that had at least 5% market share prior to the product removal.

agers, maintaining stable diversion ratios over time could indicate brand health, while sudden declines may warrant attention and potential strategic adjustments.

Differentiated loyalty patterns for major brands: Figure 9 highlights varying patterns among leading brands – Jif, Skippy, and Peter Pan – with each displaying unique loyalty trajectories. Jif's steady increase in diversion ratios reflects growing consumer loyalty, positioning it as a resilient brand in the face of product removals. Skippy and Peter Pan, however, exhibit more variability, suggesting that their consumer bases may be more susceptible to competitive pressures. These insights suggest that brands experiencing variable diversion ratios might benefit from efforts to reinforce loyalty through targeted marketing and promotions.

3.4 Explaining differences in diversion ratios

Our analysis thus far has examined the distributions of diversion ratios and their variations across different time periods and brands. In this section, we delve deeper into the factors driving these variations. Specifically, we seek to understand why some product removal events result in higher diversion ratios – indicative of stronger brand loyalty – while others yield smaller or even negative ratios, suggesting a weaker hold on consumer preference.

To explore these differences, we performed a regression analysis using the estimated diversion ratio $\widehat{D}_{jr}$ as the dependent variable. Our independent variables include three sets of variables:

1. Number of brands sold in the store, reflecting the degree of competition in the product category.

2. Shelf share of the focal brand (measured as the proportion of the brand's products out of the total product assortment in the category), representing the brand's prominence within the store.

3. Market share of the focal product within the store, providing a measure of the product's popularity before removal.

For each of these variables, we include both linear and quadratic terms in order to capture potential nonlinear effects. We also include fixed effects by brand, store, and year. This yields the following regression for a given brand j, product i, and product removal event r:

$$
\begin{aligned}
\widehat{D}_{jr} = \beta_0 &+ \beta_1 \left(\text{number of brands sold}\right)_r + \beta_2 \left(\text{number of brands sold}\right)_r^2 \\
&+ \beta_3 \left(\text{brand shelf share}\right)_{jr} + \beta_4 \left(\text{brand shelf share}\right)_{jr}^2 \\
&+ \beta_5 \left(\text{product market share}\right)_{ir} + \beta_6 \left(\text{product market share}\right)_{ir}^2 \\
&+ \xi_j + \xi_{\text{store}} + \xi_{\text{year}}
\end{aligned}
\tag{4}
$$

Table 2 presents the post-hoc regression results across five model specifications, each with varying fixed effects by brand, store, and year. This approach allows us to isolate the impact of our independent variables on diversion ratios while accounting for factors unique to specific brands or stores. The results reveal several consistent patterns across models:

U-Shaped effect of brand count: The number of brands in the store has a U-shaped effect on the diversion ratio. In contexts with a moderate number of brands, a product removal event is more likely to lead to brand switching, as consumers have several options but not an overwhelming array. For stores with either very few or very many brands, however, diversion ratios tend to be higher. In stores with limited brands, consumers are restricted in their alternatives, making it more likely they will stay loyal within the brand even after a product is removed. Conversely, in highly diversified stores, brand loyalty may be driven by the perceived uniqueness or quality of the brand, even when alternatives abound.

Inverted U-Shaped effect of shelf share: The analysis reveals that the shelf share of the focal brand has an inverted U-shaped relationship with diversion ratios. A moderate shelf share tends to yield the highest diversion ratios, implying that brands with a balanced presence can benefit the most from intra-brand loyalty when a product is removed. However, brands with either low or very high shelf shares see lower diversion ratios. Low shelf-share brands may lack sufficient visibility to foster strong loyalty, while brands with an overwhelming shelf share might saturate the market, leading consumers to experiment with competitors.

U-Shaped effect of product market share: The market share of the removed product shows a U-shaped effect on diversion ratios, indicating that the most and least popular products both retain a degree of loyalty. High market-share products contribute significantly to brand loyalty, as they tend to have dedicated consumer bases. Less popular products, while catering to niche preferences, may attract loyal consumers who remain within the brand after removal. However, moderately popular products do not exhibit the same levels of retention, potentially reflecting weaker consumer attachment.

To further interpret these results, we conducted a scenario analysis and display the results as a heatmap in Figure 10. This analysis shows how predicted diversion ratios vary as we adjust two key inputs from their 5th to 95th percentile values: the shelf share of the focal brand and the market share of the removed product. For each scenario, the number of competing brands is held constant at the median value across all removal events.

We also redo this analysis just for the larger removal events (products that had at least 5% market share). The post-hoc regression analysis is shown in Table 3, and the corresponding scenario analysis heatmap is shown in Figure 11.

The patterns observed in Figure 11 provide nuanced insights into consumer behavior and brand performance following the removal of products with substantial market share. Notably, the diversion ratios for these larger removal events are predominantly negative, indicating that brands generally lose market share when high-share products are eliminated. This finding could suggest that such high-share products are not only popular but could also serve as key anchors of consumer loyalty within the brand. When removed, these products

	Model 1	Model 2	Model 3	Model 4	Model 5
Number of brands sold	-0.351 ***	-0.392 **	-0.483 ***	-0.193	-0.205
	(0.080)	(0.171)	(0.162)	(0.121)	(0.193)
(Number of brands sold)^2	0.027 ***	0.029 **	0.035 ***	0.019 **	0.020
	(0.005)	(0.012)	(0.013)	(0.008)	(0.012)
Brand shelf share	9.229 ***	5.638	7.447 *	13.58 ***	11.31 ***
	(0.698)	(5.552)	(4.410)	(0.774)	(2.116)
(Brand shelf share)^2	-8.510 ***	-4.552	-5.532	-13.61 ***	-10.70 ***
	(0.995)	(4.449)	(4.046)	(1.199)	(2.422)
Product market share	-46.56 ***	-48.15 ***	-45.76 ***	-56.82 ***	-58.30 ***
	(1.434)	(2.825)	(3.005)	(1.540)	(4.127)
(Product market share)^2	45.55 ***	46.10 ***	42.93 ***	50.20 ***	51.33 ***
	(1.529)	(3.104)	(3.511)	(1.812)	(5.681)
Intercept	2.329 ***				
	(0.319)				
Brand fixed effect		✓	✓		✓
Year fixed effect			✓	✓	✓
Store fixed effect				✓	✓
Observations	39,905	39,905	39,905	39,905	39,905
R^2	0.032	0.040	0.046	0.117	0.121

Table 2: Post-hoc regressions for own-brand diversion ratios. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

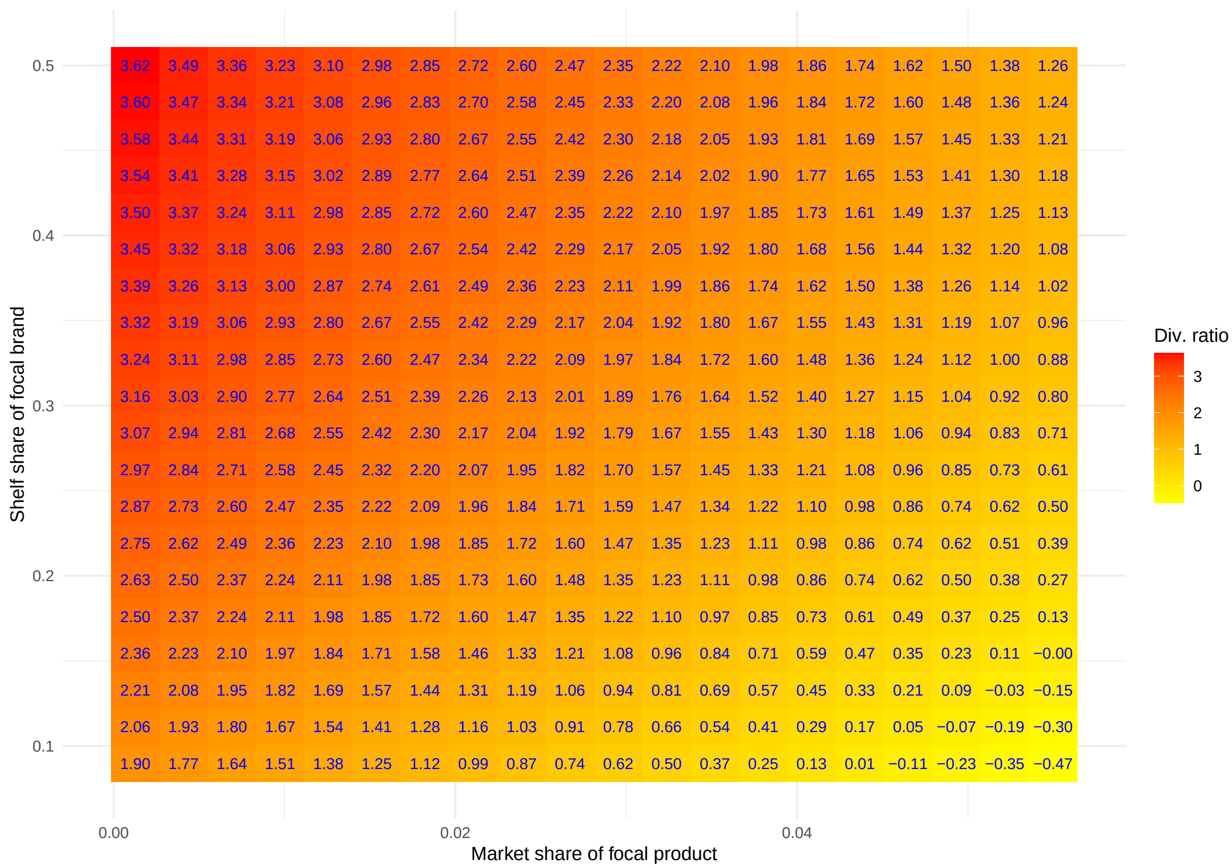


Figure 10: Heatmap of predicted diversion ratios, based on the post-hoc regression results (Model 1 in Table 2). Each cell in this heatmap corresponds to a specific combination of two variables: the shelf share of the focal brand and the market share of the focal product. Each axis includes values from the 5th to 95th percentile values of that variable.

	Model 1	Model 2	Model 3	Model 4	Model 5
Number of brands sold	-0.191 ***	-0.160	-0.187	-0.102	-0.072
	(0.060)	(0.139)	(0.107)	(0.183)	(0.149)
(Number of brands sold)^2	0.014 ***	0.012	0.013 *	0.008	0.007
	(0.004)	(0.008)	(0.006)	(0.013)	(0.008)
Brand shelf share	1.267 **	1.973 **	1.490 **	0.651	1.490
	(0.592)	(0.730)	(0.633)	(1.083)	(1.232)
(Brand shelf share)^2	-1.075 *	-1.474 *	-1.154	-0.4974	-1.010
	(0.575)	(0.810)	(0.727)	(1.042)	(1.349)
Product market share	-2.620 ***	-2.677 ***	-2.716 ***	-2.716 ***	-2.741 ***
	(0.649)	(0.342)	(0.537)	(1.408)	(1.132)
(Product market share)^2	2.011 ***	2.081 ***	2.166 ***	1.708	1.748
	(0.601)	(0.339)	(0.478)	(1.093)	(1.011)
Intercept	0.537 **				
	(0.259)				
Brand fixed effect		✓	✓		✓
Year fixed effect			✓	✓	✓
Store fixed effect				✓	✓
Observations	2,925	2,925	2,925	2,925	2,925
R^2	0.010	0.015	0.031	0.521	0.523

Table 3: Post-hoc regressions for own-brand diversion ratios for larger removal events (products that had at least 5% market share). Significance levels: *p<0.1; **p<0.05; ***p<0.01

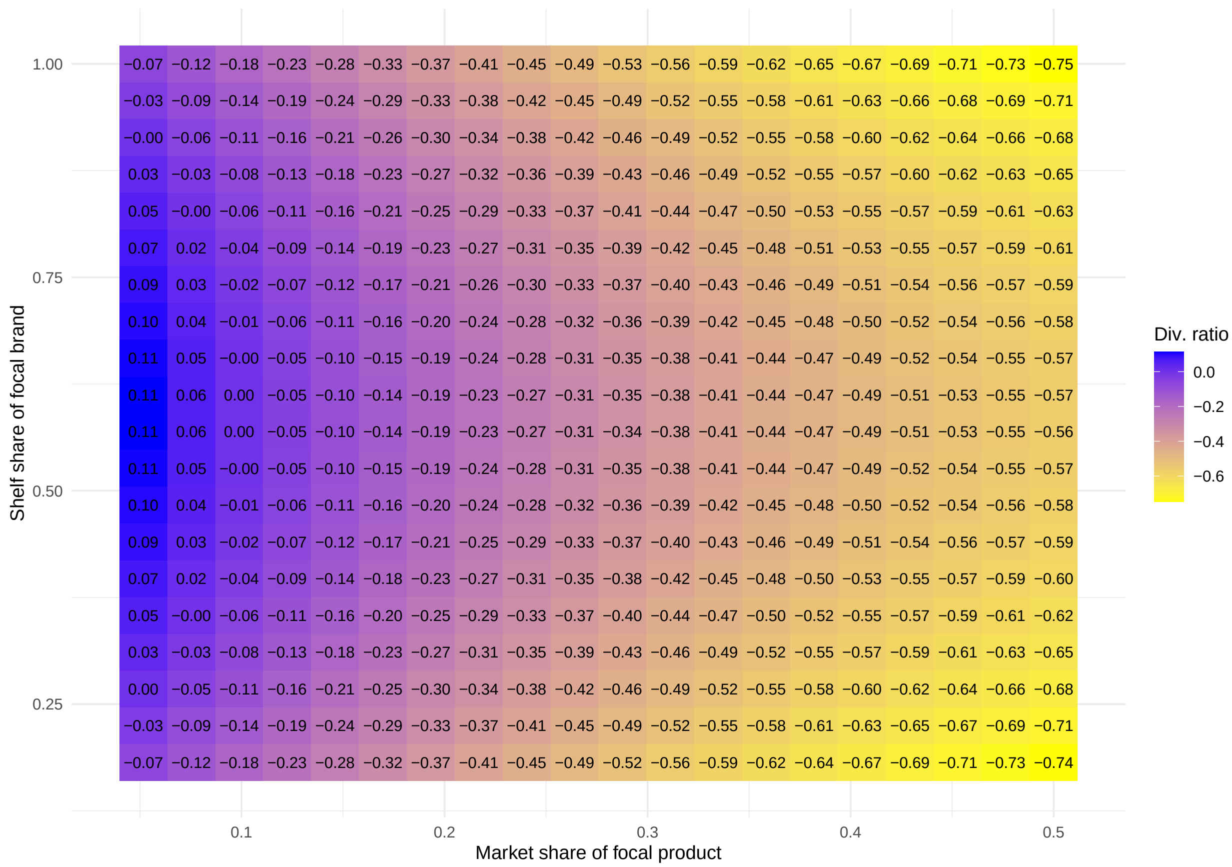


Figure 11: Heatmap of predicted diversion ratios, based on the post-hoc regression results for larger removal events (Model 1 in Table 3). Each cell in this heatmap corresponds to a specific combination of two variables: the shelf share of the focal brand and the market share of the focal product. Each axis includes values from the 5th to 95th percentile values of that variable for larger removal events (products that had at least 5% market share).

leave a gap that is not easily filled by other items within the brand's portfolio, leading to a higher likelihood of consumers switching to competing brands.

An additional finding is the nonlinear relationship between the brand's shelf share and the diversion ratio. Specifically, diversion ratios are highest for brands with moderate shelf share, while both low and high shelf shares lead to reduced retention rates. Brands with moderate shelf shares may strike the optimal balance between visibility and variety, encouraging consumers to explore alternative products within the same brand when a preferred item is removed. In contrast, low shelf share brands may struggle to retain consumers due to reduced visibility and fewer substitution options within the brand, and high shelf share brands might saturate the category, diminishing the uniqueness or differentiation of individual products and potentially driving consumers to competitors when a product is removed.

Our findings from this scenario analysis suggest actionable strategies for brand and store managers:

Optimize shelf space allocation: The inverted U-shaped effect of shelf share on diversion ratios implies that brands should aim for an optimal shelf presence. Excessive shelf space allocation may dilute brand appeal, while insufficient presence reduces consumer awareness and loyalty. Brands could work with retailers to identify this optimal share, ensuring their products are visible enough to drive loyalty without overwhelming consumers.

Maintain high-impact products: High market-share products play a critical role in brand retention after a removal event, as shown by their positive relationship with diversion ratios.

Leverage niche products for retention: Although niche, lower-market-share products attract fewer buyers, those consumers tend to exhibit stronger loyalty. Brands can use this insight to retain niche products in their lineups, particularly in competitive store environments.

4 Discussion and conclusion

In this study, we demonstrate the value of diversion ratios as a tool for understanding consumer responses to product removal events in retail settings and using it as a brand performance monitoring tool. Rather than establishing causality, our goal is to describe data patterns that offer novel insights into brand loyalty and consumer substitution behavior. Diversion ratios, as we demonstrate, provide managers with an accessible, interpretable, and nonparametric method to monitor and interpret shifts in demand post-product removal without requiring extensive data or restrictive modeling assumptions.

4.1 Diversion ratios as a localized brand performance monitoring tool

Diversion ratios hold considerable value as a practical measure for brands assessing product line management strategies. By observing how a brand's share shifts in response to a product's removal, brands can gauge whether their product elimination decisions align with strategic goals such as maintaining brand loyalty and minimizing consumer defection. This approach stands out as an alternative, cost-effective method to traditional brand performance metrics, such as customer surveys or preference-based models, which can be costly, time-consuming, and sometimes skewed by survey biases. Moreover, diversion ratios are derived from store-level data, eliminating concerns over privacy issues that often arise with individual-level data collection, while still providing accurate insights into consumer behavior.

Our approach also encourages a shift toward localized, store-level monitoring of brand performance. In contrast to aggregate metrics, store-specific diversion ratios reveal the nuances of brand loyalty at the local level, which can vary widely across different regions or demographics. By focusing on store-level dynamics, brands and retailers can adopt more nuanced and data-driven approaches to their assortment strategies, ensuring that product removals reflect local consumer loyalty trends and preferences.

4.2 A guide for brands to identify assortment opportunities

Our analysis also serves as a strategic guide for identifying assortment opportunities. Specifically, the post hoc analysis presented in this study reveals patterns that can inform future product line decisions. For instance, brands with moderate shelf shares tend to have higher diversion ratios, indicating that maintaining a balanced shelf presence could optimize loyalty retention without overwhelming consumers. Additionally, our findings on the U-shaped relationship between product market share and diversion ratios suggest that niche products with dedicated followings, as well as high-share products, play significant roles in retaining consumer loyalty.

Brands can use these insights to design assortment strategies that prioritize high-impact products with established loyal followings. For example, niche or low-market-share products that exhibit strong intra-brand retention might be retained to cater to specific consumer segments, while mid-range products with less loyalty impact could be reconsidered. This approach not only optimizes shelf space but also aligns with evolving consumer preferences toward curated, relevant assortments.

4.3 Nonlinear effects

Our findings highlight nonlinear effects in how assortment size, brand visibility, and consumer loyalty interact. The inverted U-shaped relationship between shelf share and diversion ratios indicates that brands with moderate shelf space retain the most loyalty. Too little shelf space limits visibility and substitution opportunities within the brand, while too much can dilute perceived differentiation and push consumers toward competitors.

Similarly, the U-shaped relationship between the number of brands in a store and diversion ratios reveals that stores with very few or very many brands retain loyalty better than those with moderate brand counts. In stores with fewer brands, limited alternatives drive intra-brand substitution. In highly diverse stores, familiar brands stand out and foster retention, while stores with moderate diversity see more switching.

For managers, these patterns suggest actionable strategies to optimize product assortments and shelf space allocation. Brands with moderate shelf shares achieve the best outcomes by balancing visibility and variety without oversaturating shelves, ensuring that their presence is strong enough to encourage substitution without overwhelming consumers. In stores with fewer competing brands, managers should focus on retaining key products that are critical for loyalty retention, as fewer alternatives increase the reliance on existing assortments. Conversely, in stores with high brand diversity, brands should prioritize distinctiveness and differentiation to capture loyalty in a crowded competitive environment.

4.4 Dollar quantification and economic impact

To quantify the short-run financial effects of product removal events, we can calculate the dollar change in revenue for different product removal events. The short-run dollar change in revenue for brand j's removal event in store r is the average price multiplied by the change in units sold: $\overline{price}_{jr}\left(q_{jr}^{\text{post}} - q_{jr}^{\text{pre}}\right)$.

We assume that the category sales volume is stable in the short-term, and to account for differences in package sizes, we normalize both the prices and the sales quantities using a 16 oz baseline. This allows us to derive an expression for the short-run dollar change in revenue based on our definition of the diversion ratio (Equation 3):

$$
\begin{aligned}
D_{jr} &= \frac{s_{jr}^{\text{post}} - s_{jr}^{\text{pre}}}{s_{ir}^{\text{pre}}} \\
(D_{jr})\left(s_{ir}^{\text{pre}}\right) &= s_{jr}^{\text{post}} - s_{jr}^{\text{pre}} \\
\underbrace{\left(q_{jr}^{\text{pre}} + \sum_{k \neq j} q_{kr}^{\text{pre}}\right)}_{\text{category sales}} (D_{jr})\left(s_{ir}^{\text{pre}}\right) &= q_{jr}^{\text{post}} - q_{jr}^{\text{pre}} \\
\overline{price}_{jr}\left(q_{jr}^{\text{pre}} + \sum_{k \neq j} q_{kr}^{\text{pre}}\right) (D_{jr})\left(s_{ir}^{\text{pre}}\right) &= \underbrace{\overline{price}_{jr}\left(q_{jr}^{\text{post}} - q_{jr}^{\text{pre}}\right)}_{\text{dollar change in revenue}} \qquad (5)
\end{aligned}
$$

For a prototypical product removal event, we can calculate the expression on the left side of Equation 5 using the median diversion ratio and median sales quantities, and we find that the short-run dollar change (for weeks 2-5 after the removal event) is about $300. To examine these patterns further, we consider a handful of exemplar scenarios focusing on two brands (Jif and Laura Scudder) where the removed product is either popular or unpopular, the store is either large or small, and the diversion ratio is either low or high.

The result from this comparison are shown in Table 4, and we find a number of interesting patterns. First, we find that low diversion ratios generate losses in revenue while high diversion ratios generate gains in revenue: the left side of the table shows negative dollar changes and the right side of the table shows positive dollar changes across all combinations of brand, store size, and product popularity. Second, the dollar changes are smallest in magnitude when the store is small and the product is unpopular, and examining scenarios with a larger store and/or a more popular product will magnify the dollar change. Finally, the dollar changes are also larger in magnitude across the board for Jif (the larger brand we consider) compared to Laura Scudder (the smaller brand). These findings highlight the interconnected role of store size, product popularity, and brand scale in determining revenue outcomes after product removal.

	Brand: Jif			
	Low diversion ratio		High diversion ratio	
	Unpopular product	Popular product	Unpopular product	Popular product
Small store	-$30	-$540	$58	$1028
Large store	-$207	-$3687	$395	$7013

	Brand: Laura Scudder			
	Low diversion ratio		High diversion ratio	
	Unpopular product	Popular product	Unpopular product	Popular product
Small store	-$12	-$89	$21	$162
Large store	-$61	-$459	$110	$829

Table 4: Estimated dollar change in revenue after a hypothetical product removal event. All dollar values are calculated for a representative brand-store-week combination based on Equation 5. Low and high diversion ratios are defined based on the diversion ratios for a particular brand (10th percentile and 90th percentile, respectively). Small and large stores are defined based on their total category sales volume for peanut butter (10th percentile and 90th percentile, respectively). Unpopular and popular products are defined based on the market share of the removed product (10th percentile and 90th percentile, respectively).

4.5 Managerial implications

Our findings bear practical and actionable implications for both brand managers as well as retail-store managers engaged in product assortment planning and brand negotiations. In today's highly competitive retail environment, retail managers are increasingly tasked with making decisions on product retention, promotion, and removal, and these choices often require a balanced consideration of performance metrics and strategic goals. Diversion ratio analysis offers a quantitative and actionable tool for managers to make product line decisions that align with both retail and brand objectives, thereby enhancing overall store performance and consumer satisfaction.

By employing diversion ratios, retail managers can move beyond subjective or anecdotal decision-making processes. Instead, they gain a real-time, evidence-based framework. Tracking diversion ratios over time enables managers to monitor consumer loyalty dynamics, providing insights into which products are essential for sustaining brand loyalty and which items contribute minimally.

In collaborative discussions with brand representatives, diversion ratios can serve as a concrete metric for justifying product assortment decisions. Retail managers frequently negotiate with brands over which items should be prioritized, expanded, or phased out, based on performance data and strategic alignment. Diversion ratios allow these conversations to be grounded in quantifiable consumer loyalty measures, supporting informed decision-making around shelf allocation and product lifecycle management. For instance, a product with a high diversion ratio following the removal of a similar item can be highlighted as a priority for expanded shelf space, given its demonstrated capacity to retain consumer demand. Conversely, products with low diversion ratios, which may not contribute substantially to brand loyalty, can be candidates for reduction or replacement.

Additionally, diversion ratio analysis enables managers to take a location-specific approach to assortment planning by examining these ratios across different stores. This localized perspective is particularly valuable in retail chains where consumer preferences may vary widely depending on regional or demographic factors. Diversion ratios provide managers with insights into the unique demand patterns of each store's clientele, allowing them to tailor their assortments accordingly. For example, if a product exhibits high loyalty retention in one location but low retention in another, managers can make targeted adjustments to maximize brand presence in areas with the strongest consumer response. This data-driven approach not only optimizes assortment efficiency but also aligns with the growing trend toward personalized and location-sensitive product strategies, ensuring that each store's offerings are attuned to its specific consumer base.

Further, diversion ratios provide insight into the life cycle of products within a brand. Products with initially high diversion ratios that diminish over time might indicate waning consumer interest, signaling an opportunity for product refreshment or replacement. Conversely, products that maintain stable or growing diversion ratios over time demonstrate enduring appeal, marking them as candidates for further investment. This life cycle perspective allows managers to make forward-looking assortment decisions that support long-term brand health and consumer loyalty.

The insights gained from diversion ratios also serve to strengthen retailer-brand relationships. Brands benefit from understanding which of their products maintain loyalty and drive within-brand substitution post-removal, while retailers gain confidence in selecting products that align with store performance goals. This data-driven alignment fosters a more strategic, collaborative relationship, enabling both parties to co-create assortment strategies that enhance profitability and brand presence while prioritizing consumer satisfaction.

4.6 Limitations and future directions

While our study offers valuable insights into consumer behavior and brand performance following product removals, it is not without limitations. These limitations provide avenues for future research that could build on our findings and further deepen our understanding of brand loyalty and consumer substitution patterns.

4.6.1 Applicability to existing brands and stores

The first limitation arises from the nature of our data and the non-parametric model we employ, which focuses on established brands and existing store locations. Our approach relies on historical store-level data to measure shifts in consumer demand in response to product removal. Consequently, while the findings and patterns derived from diversion ratios are robust for existing brands within known store contexts, they do not extend predictively to new brands, products, or store types not represented in our dataset. For example, diversion ratios calculated may not transfer directly to new entrants, emerging product categories, or different retail formats.

4.6.2 Exogenous variation in product removals

An additional limitation of our study is the reliance on observational data, which does not permit airtight causal inference. Ideally, to truly measure consumer response to product removal, a brand would need to conduct a randomized experiment wherein the same product is systematically removed in some stores but left in others to create exogenous variation. This would provide the cleanest measure of consumer response to a product's absence by isolating it from other market fluctuations or competitive actions. Obviously, this approach is practically infeasible in real-world retail settings because of risks of immediate revenue loss, operational constraints and competitive risks.

Given these challenges, future research could explore creative alternatives to randomized experiments, potentially using hybrid models that integrate both existing data and limited, targeted market trials to enhance predictive validity.

However, these concerns about endogeneity do not invalidate the usefulness of our method as a descriptive tool for brands and retailers. The diversion ratios represent consumer responses to product removals, so our proposed method can serve as a way for brands and retailer sto monitor how successful their product removals have been.

4.6.3 Potential bias in capturing niche brand loyalty

Our analysis primarily focuses on diversion ratios as an indicator of consumer loyalty, yet it may not fully capture nuanced loyalty dynamics, especially in cases of niche products with dedicated but small consumer bases. Products with low overall market share may still possess a loyal customer segment, which could be undervalued in our model if these products do not generate substantial category share. Future research could examine segmentation techniques within the diversion ratio framework, differentiating between mainstream and niche products to identify potential biases in measuring loyalty. This could enable brands to make more informed decisions about retaining items that hold niche appeal but may be at risk of removal due to their smaller consumer footprint.

4.6.4 Understanding other contextual drivers for changes in diversion ratio

Our study provides a brand performance monitoring tool and as an alternative method to measuring and track brand loyalty. While it provides implications based on brand, product, and retailer characteristics, it is limited for explaining the dynamics in diversion ratio over time. Consumer loyalty patterns may shift in response to new products, changing tastes, advertising, changing economic conditions, or competitive actions. Future studies could integrate data from other sources that tap into these factors, to offer more explanation of how loyalty evolves over time and how brands can adapt their strategies accordingly.

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