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The evolving role of hit and niche products in brick-and-mortar retail category assortment planning: A large-scale empirical investigation of U.S. consumer packaged goods

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ABSTRACT

Long tail theory, the notion that the future of retailing could involve shifting product assortments to offer more product variety to precisely serve the unique needs of individual customers, has largely been proven true in the context of online distribution. However, it has been implicitly assumed that this theory does not apply to brick-and-mortar selling situations due to higher supply side inventory costs and higher demand side consumer search costs. Academics and practitioners alike have thus advocated for the use of Pareto rules to make category assortment planning decisions about product inventory breadth and depth in the brick-and-mortar channel. This research directly challenges this received wisdom by noting that the widespread prevalence and use of mobile technology is causing information flows to speed up for consumers even while performing traditional shopping tasks. Such information flows should theoretically favor the strategic importance of niche products in the long tail of the sales distribution. A large-scale empirical analysis of consumer packaged goods brick-and-mortar retailing data indicates that this alternative prediction is indeed true. This research contributes to a larger body of research as well that has documented how major environmental forces are shifting the nature of retail strategy, particularly in the brick-and-mortar channel.

1. Introduction

Major environmental forces including technology, competition and globalization are fundamentally changing retail landscapes in important ways (Baier and Stüber, 2010; Paul and Rosenbaum, 2020), and brick-and-mortar retailers are likely to experience the greatest levels of disruption (Azeem et al., 2019; Badrinarayanan and Becerra, 2019; Helm et al., 2020). Notably, consumers are increasingly making their customer journey in a multi-channel context, utilizing a mix of digital and traditional methods to search for information, to shop, and to ultimately make purchase decisions (Cao and Li, 2015; Harris et al., 2018; Hu and Tracogna, 2020). Fully online and multi-channel retailers are gaining increasing power and relevance in the marketplace at the expense of traditional retailers as a result (Kaatz et al., 2019; Pantano and Pizzi, 2020; Tang and Xing, 2001; Verhoef et al., 2015).

To remain relevant, brick-and-mortar retailers must leverage known channel advantages such as hedonic shopping benefits (Ballantine et al., 2010; Childers et al., 2001; Yim et al., 2014), customer loyalty to a distinct store brand offering (Hoskins, 2016; Huang and Feng, 2020; Liu et al., 2018), and the ability of customers to conveniently touch, feel, and experience products (Gahinet and Cliquet, 2018; Pantoja et al., 2020), while also adapting to changing conditions in innovative and strategic ways (Pantano and Vannucci, 2019). Brick-and-mortar retailers may need to re-think a variety of strategic decisions that include, but are not limited to: pricing, promotional support, service support, and product strategy.

This study looks to focus in on one such major brick-and-mortar retail decision that has drawn considerable previous research attention: category assortment planning, which involves the breadth and depth of distribution for products and brands in the retail outlet’s product categories (Kahn et al., 2014; Mantrala et al., 2009). In particular, the literature gap that is sought to be filled by this research is how evolving consumer capabilities and behaviors associated with increased information flows (Shankar et al., 2016; Wang et al., 2015) may be changing the strategic respective roles of hit (high popularity/high market share) and niche (low popularity/low market share) products over time. While previous empirical inquiries have shown that a few leading brands and products command an overwhelming proportion of brick-and-mortar retail sales in a given product category (Kim et al., 2017; Tanusondjaja et al., 2018), it is argued here that these traditional
sales distributions of products within a category are likely to shift to include a more uniform distribution as more consumers can easily learn about less popular niche product offerings in real time with the aid of mobile technologies (Huang et al., 2009; Lamberton and Stephen, 2016). It has been well established in online contexts that niche products benefit most from increased information flows due to their low rates of brand awareness (Ho-Dac et al., 2013; Hoskins and Brown, 2018; Zhu and Zhang, 2010), and it is extrapolated here that a similar dynamic may be emerging in brick-and-mortar contexts, given evolving consumer search capabilities and behaviors.

It must be conceded that previous authors have empirically demonstrated (Bell et al., 2012; Choi and Bell, 2011; Brynjolfsson et al., 2011) that online retail channels typically experience more uniform category level sales distributions due to similar arguments about consumer search capabilities coupled with arguments about lowered costs of supply. However, these studies use the brick-and-mortar channel as the control group upon which to compare the online channel against, as it is typically assumed that these supply- and demand-side efficiencies are not present in the brick-and-mortar channel (Anderson, 2006; Brynjolfsson et al., 2006; Kim et al., 2017). It is argued here that such an assumption is becoming less accurate, as Internet consumer search capabilities are increasingly available to and in use by consumers with mobile technologies before, during, and between physical store shopping trips (Huang et al., 2009; Lamberton and Stephen, 2016).

Should it be shown empirically that long tail theory (Anderson, 2006; Brynjolfsson et al., 2006), or the fundamental argument that retailers may find success offering wider product variety to more precisely serve a heterogeneous base of customer needs instead of relying on the sales of a few hit products alone, may apply to brick-and-mortar retailing contexts as well, it would represent a major shift in academic and practitioner viewpoints. Recent empirical studies (Kim et al., 2017; Tanusondjaja et al., 2018) have directly confirmed that brick-and-mortar retailers typically experience Pareto sales distribution (where about 80% of sales are generated by about 20% of products) in their product categories that they serve, while managers are known to apply Pareto rules to set category assortments (Chen et al., 1999; Mantrala et al., 2009; Reibstein and Farris, 1995). This paper looks to revise the received wisdom on the topic by noting that, while Pareto rule distributions are likely present in the brick-and-mortar channel on average, they are becoming less applicable over time. Niche products are commanding an increasing amount of market share and retail managers should shift their category assortment planning strategy accordingly. The relevant literature is reviewed next, followed by an overview of the methodological approach, a reveal of the empirical results, and then a discussion of the key outcomes of the research.

2. Theoretical development

2.1. Long tail theory: Application to the online channel

The long tail theory of assortment strategy for online retailers gained both academic (Brynjolfsson et al., 2006) and popular press (Anderson, 2006) intrigue just over a decade ago. The accounts provided in both arenas fundamentally argued that the future of retailing in the online channel would involve an increased focus on providing a larger assortment of product offerings to consumers and that this strategy would be viable for two underlying reasons. First, the online channel allowed for lower costs of supply (Anderson, 2006; Brynjolfsson et al., 2006). Second, consumers in this channel would benefit from lowered search costs making it easier to find obscure offerings leading to elevated demand functions for the less popular (commonly referred to as niche) products (Anderson, 2006; Brynjolfsson et al., 2006). While some academic skepticism about this theory arose at first (Boyd and Bahn, 2009; Elberse, 2008), empirical evidence has since generally supported the long tail view in the online context (Bell et al., 2012; Choi and Bell, 2011; Brynjolfsson et al., 2011).

2.1.1. Lowered supply costs for online retailers

Producers can indeed justify selling a wider variety of products online due to lower supply chain and selling costs (Brynjolfsson et al., 2003), which stem from the retailer’s ability to limit the need to hold inventory in physical stores for consumers. By instead keeping products in warehouses and building more centralized and responsive distribution systems, online retailers can leverage lower costs of supply to justify the choice to offer a wider product assortment to consumers which may make it possible to generate more sales from the tail end of the category’s sales distribution. These lowered cost structures for firms also translate into lower prices for customers (Brynjolfsson and Smith, 2000).

2.1.2. Lowered consumer search costs’ impact on online markets

Ease of information search and the breakdown of information asymmetry have long been theorized to shift the power balance from producers to consumers, leading to lower prices (Anderson and Renault, 1999; Bakos, 1997; Diamond, 1971; Wolinsky, 1986). The empirical evidence in support of these claims is quite strong. Availability of online information about wines led to lowered search costs, which served to decrease price sensitivity (Lynch and Ariely, 2000). Brown and Gooldshee (2002) found lower prices for insurance made available online due to consumers’ newfound ability to search and compare rates for similar policies. Zettelmeyer et al. (2006) also found lower automobile prices in the online channel and concluded that the transparency of information about prices provided to consumers was the main cause.

Search costs for consumers have only lowered as technological advances have increased the usefulness of available tools. Due to advances in information technology (including the growth of search engine availability and the prevalence of social media), consumers can engage in online search about products with lowered effort and money expended (Brynjolfsson et al., 2010). Product recommendation systems and the ability to directly acquire information about products help facilitate a fluent information search process, which leads to higher rates of sales conversions (De et al., 2010).

2.1.3. Evidence of long tail growth in the digital channel

Perhaps as a result of these conditions, online retailers have been found to offer a much wider assortment of products than brick-and-mortar counterparts. Elberse (2008) reports a greater number of available titles for online music and movies. When compared to a typical large brick-and-mortar store serving the category of interest, Brynjolfsson et al. (2003) report that a large online retailer achieves about 40–50% of its total sales from the array of titles that are not popular enough to be carried by the brick-and-mortar store: the online retailer also generally carries 20-50x more titles per category.

Although not as stark, differences are also apparent between the online channel and other offline channels such as catalogs. It is important to note that an offline catalog possesses the same supply side efficiencies as an online channel, so the only remaining differentiator may be the consumer search cost structure. Even still, Brynjolfsson et al. (2011) found that the long tail of the distribution (tested as the bottom half of products by sales volume) accounted for significantly more share of sales in the online channel than for the offline catalog of the same firm. About a 20–25% relative increase in sales from the long tail was observed in the Internet channel. As the offline catalog removes the supply side costs, one would assume such a comparison between a between the online channel and a brick-and-mortar channel for the same retailer would be much higher.

Additional studies on the influence of online word-of-mouth across a number of other industry contexts have further substantiated the core result that online information flows have more influence on low popularity/sales (niche) products than on high popularity/sales (hit) products (Ho-Dac et al., 2013; Hoskins and Brown, 2018; Zhu and Zhang, 2010).
2.1.4. Strategic benefits of investing in the long tail for online retailers

The long tail provides clear strategic value for retailers in the online channel. Low popularity products generally have higher prices, less discounting and lower price elasticity (Brynjolfsson et al., 2003). These less popular niche products also receive disproportionately high click activity in the online channel in response to promotional efforts (Tucker and Zhang, 2011). Lastly, while niche products are generally unpopular among the mass market of available consumers, these products are especially liked by a small segment of consumers leading them to be particularly fervent and, as a result, loyal customers (Clemons et al., 2006). By no longer being forced to settle for a less well-suited product, niche market customers become substantially more satisfied with and loyal to an online retailer that offers their most preferred product(s) (Cachon et al., 2008).

2.1.5. Competing arguments and findings (superstars and choice overload)

It is important to concede, however, that a couple of key arguments do persist in the literature, which bring some doubt to the strategic value of the long tail. The first argument is that of choice overload, perhaps most well known by the seminal work of Iyengar and Lepper (2000), which posits that too many options within a product assortment has the potential to overwhelm a consumer. The second argument is that of the superstar product, which is a product that may dominate a market due to higher quality and scale efficiencies (Rosen, 1981). The most popular products in a category indeed generally enjoy both share and loyalty advantages over less popular products (Ehrenberg et al., 1999; Fader and Schmitt, 1993).

Frank and Cook (1995) argued that the Internet’s increased information flow would lead to the growth of winner-take-all markets where superstar products achieve greater dominance because of the ability to more easily find and identify the best product offering in a certain category. Some more recent empirical investigations that focus on the online channel have revealed increased support for this basic hypothesis. For example, Noe and Parker (2005) suggest that the returns in many markets have tilted towards winner-take-all settings, where leading firms and leading products in an industry disproportionately grow and dominate sales. Fleder and Hosanagar (2009) suggest that recommender systems in the online retailing setting may favor superstar products leading to further growth in the sales of these already dominant products. In empirical investigations of digital music and movies, Elberse (2008) finds that consumers report lower post-purchase satisfaction after consuming less popular products and that a large number of newly available titles in the digital channel register no sales. The unbundling of albums into individual tracks or smaller sets of tracks in the music industry to serve the digital channel led to decreased overall revenue, probably because consumers placed lower value on less popular songs and now extracted more customer value by buying only the hits (Elberse, 2010).

Perhaps in a successful merging of the two competing perspectives (long tail vs. winner-take-all effects), Brynjolfsson et al. (2010) noted the following: “Sites like Amazon include recommendation engines, which help consumers find products in the Long Tail, as well as prominent links to lists of top sellers in each product category, which tend to increase winner-take-all effects. What’s more, it is possible...could increase the relative size of both the head and the tail...at the expense of the middle (of the distribution).” Perhaps a bit tangential, but a similar scenario has unfolded in regards to the simultaneous rise of globalization and localized production/consumption activity (Marquis and Battilana, 2009). Increasing information flows worldwide seem to be favoring the growth of both leading and specialty products across many markets.

2.2. Application of long tail theory to the brick-and-mortar channel

The central focus of this research, of course, is to determine whether long tail theory, which has clearly gained some theoretical and empirical traction in the context of online retailing, is increasing in its applicability to the brick-and-mortar channel over time. The viewpoint of the field to date has generally been a resounding “no”: indeed, many empirical investigations use the brick-and-mortar channel as the control condition to compare the online channel to, in order to identify potential evidence of long tail effects (Kim et al., 2017). The accepted reasoning of the extant literature is reviewed next, before it is extended substantively to generate key hypotheses of interest.

2.2.1. The pervasive acceptance of traditional pareto rule arguments by academicians and managers

Brick-and-mortar retailers have long been known to heavily emphasize a few leading products in their assortment planning in the hopes of maximizing sales and profit outcomes: many managers apply a Pareto rule heuristic in this process (Chen et al., 1999; Mantrala et al., 2009; Reibstein and Farris, 1995). Assumed higher supply costs and higher consumer search costs have largely led brick-and-mortar retailers to continue to restrict the size of their product assortments (Bell et al., 2012; Choi and Bell, 2011).

Quite recently, Kim et al. (2017) conducted a large scale empirical analysis of consumer purchase data over a 6 year period, with an analysis sample of ~18,000 households who purchased 238 brands across 22 product categories: they concluded that the Pareto rule is a generally sound assumption in the brick-and-mortar channel and thus could be conceived of as an acceptable empirical generalization for the field. Tanusondjaja et al. (2018) also found similar empirical results with a different dataset and level of aggregation (products instead of brands) in their analysis. In further support, Hoskins and Griffin (2019) recently showed that large and powerful established fast moving consumer goods’ brands experience substantial sales performance advantages in bringing new products to the marketplace and that both retail manager and end consumer adoption rates are higher. Bogomolova et al. (2019) also showed that consumers shopping baskets on a typical store trip is filled with about 95% of brands that they have purchased on previous store trips.

In motivating the need to empirically examine the presence of the Pareto rule for consumer packaged goods in the brick-and-mortar context, Kim et al. (2017) referenced how a related stream has “examine(d) the Internet’s ‘long tail’ phenomenon, which describes how sales of niche products can grow to take over a larger share of the market than (they) might otherwise have in a purely bricks-and-mortar world”. They, as most authors have done, clearly took the perspective that long tail theory would apply only to the online channel, as the conditions of products to make available for all customers. Therefore, the authors in this paper have focused on the online channel to identify potential evidence of long tail effects (Kim et al., 2017). The accepted reasoning of the extant literature is reviewed next, before it is extended substantively to generate key hypotheses of interest.
2.2.3. The presumed impact of elevated consumer search costs

The received wisdom to date has been that consumer search costs are considerably higher in the brick-and-mortar channel as well. This assumption is directly challenged here, with the support of key recent literature developments. While this assumption was likely safe in the past, retail conditions have evolved substantially in more recent times. Access to information is speeding up as tools such as the Internet are increasingly becoming common for consumers worldwide (Brown and Goolsbee, 2002; Huang et al., 2009). More recently, many tools to enable quicker and easier consumer search have been converted from desktop computers to a myriad of mobile devices such as smart phones and tablets (Lamberton and Stephen, 2016; Wang et al., 2015).

Recent empirical evidence has directly linked the use of mobile devices as tools for consumer search during purchase decisions in brick-and-mortar stores (Shankar et al., 2016). Consumers are also increasingly extending the consumer search and shopping process across multiple traditional and digital channels over time, enabling information flows to further link from the digital to the brick-and-mortar retail channel (Swaminathan et al., 2020). Recalling that increased information flows favor the sales performance expectations of lower popularity/niche products (Ho-Oac et al., 2013; Hoskins and Brown, 2018; Zhu and Zhang, 2010), it is predicted that:

**H1.** Low (high) sales rank products in consumer packaged goods categories are experiencing higher (lower) sales growth rates over time in the brick-and-mortar retail channel.

2.2.4. Why the long tail could strategically matter in the brick-and-mortar channel

If this supposition is indeed right, and search costs are lowering in general across all channels of distribution, there could be significant ramifications for optimal strategy among brick-and-mortar retailers. A sizeable body of research has demonstrated that providing sufficient category assortment variety to consumers could be beneficial for the overall success of the brick-and-mortar retailer. Providing more variety, and specifically a unique set of products in the assortment, allows a retailer to differentiate itself from its competition (Mantrala et al., 2009). By offering a sufficient amount of category variety, the brick-and-mortar retailer is able to satisfy heterogeneous demands of its customer base (Cachon et al., 2005). Failing to stock a customer’s first choice brand or product significantly increases the odds that no purchase in the category will be made (Boatwright and Nunes, 2001). Efforts to increase short term profitability by reducing assortment size run the risk of alienating a retailer’s customer base that demand some level of variety in their choices for each store visit (Rust et al., 2000). Such customer alienation can reduce the likelihood of future store patronage as well (Briesch et al., 2009; Campo et al., 2004).

Choi and Bell (2011) showed that, in the case of diapers, niche brand loyal consumers are liable to switch from the brick-and-mortar channel to the online channel when their preferred brand was not reliably available in their local physical store. A number of additional studies have corroborated the degree of competition taking place between brick-and-mortar and online stores (Anderson et al., 2010; Brynjolfsson et al., 2009; Forman et al., 2009; Son et al., 2017). Offering a sufficient level of product variety thus serves as an important competitive tool for brick-and-mortar retailers to fend off increasing competition from traditional and online competitors alike.

Together, it seems that the assumption that the long tail is incompatible with the brick-and-mortar channel is potentially outdated. It is quite likely that the long tail of the distribution has been increasing in strategic importance over recent years for brick-and-mortar retailers, due to decreasing search costs for consumers and increasing rates of retail competition. Thus:

**H2.** Long tail product offerings are becoming more strategically relevant for retail managers over time in the brick-and-mortar retail channel.

2.2.5. The role of cross-category consistency in category assortment strategy

It is lastly posited that a retailer’s effort to expand category assortments to include more products from the long tail of the sales distribution is likely to be most successful when it is consistently deployed across product categories. In doing so, a retailer is more likely to establish a strategic orientation and market image that is consistent with the types of consumers that may opt to buy less popular, niche market offerings typically found in the tail end of the sales distribution (Hwang and Chung, 2019; Lombart et al., 2018). Indeed, it is also well established that customers who prefer niche product offerings in certain product categories tend to extend that preference across other product categories (Noy, 2010; Schaefers, 2014). Maintaining consistency across product categories has generally been found to be important for retailers along a number of strategy dimensions (Russell and Petersen, 2000), such as private label branding (Sebri and Zaccour, 2017) and pricing (Janakiramam et al., 2006). Together, it is expected that a similar dynamic will hold here in regards to the category assortment variety levels across product categories. Therefore:

**H3.** The positive sales returns to a long tail retailing strategy in the brick-and-mortar retail channel will be highest when a consistent commitment is made across the retailer’s product categories.

3. Methodological approach

3.1. Data

3.1.1. Data source and description

To test the hypotheses of interest, data from the Information Resources, Inc. (IRI) marketing dataset are utilized (Bronnenberg et al., 2008). These data include sales, distribution and marketing data for individual Stock Keeping Units (SKU’s) across a sample of U.S. grocery and drug store retail outlets from 2001 to 2011. Data are included in weekly periods and were collected by point of sale technology in individual stores that participated in the data sharing agreement. Thirty-one product categories are included in the data spanning a variety of food and non-food fast moving consumer packaged goods (FMCG’s). The IRI marketing dataset has been made available to interested empirical researchers at a reasonable purchase price and has supported at least two hundred academic publications to date on a variety of topics spanning pricing, product management, retailing, branding, and other inquiries of interest (Kruger, 2017). This robust secondary dataset was acquired through a project proposal and associated payment to support this research project and additional projects. The only additional data source that was used in this study is the publicly available U.S. Consumer Price Index, gathered from the Bureau of Labor Statistics.¹

3.1.2. Sample identification and data aggregation

The raw form of these data includes weekly sales for individual stock keeping units (SKU’s) for each individual store outlet. In total, across the thirty-one product categories, there are about 2 Billion total observations in the raw dataset. For the purposes of this research, the data are aggregated upwards to three levels of interest: (a) the SKU-Category-Year level, (b) the Store-Category-Year level, and (c) the Store-Year level.

The SKU-Category-Year level of aggregation allows H1 to be tested: the prediction that niche products in the tail end of the sales distribution will experience higher sales growth rates over the observation time period (spanning from 2001 to 2011) than hit products will. The SKU-Category-Year level of aggregation is achieved by first collapsing data for individual SKU-store combinations from the weekly to yearly level,

¹ [https://www.bls.gov/cpi/](https://www.bls.gov/cpi/)
before then collapsing all individual stores up to the national level. This analysis investigates how individual SKU’s perform year-on-year across the entire United States. This provides an analysis sample of 663,888 unique observations after accounting for missing data omissions.

The Store-Category-Year level is a second level of aggregation used in reported analyses as it allows a direct test of H2: that long tail products will become more strategically relevant to retail managers over time. While H1 took the viewpoint of the niche product itself, H2 takes the viewpoint of the retail manager and how the niche product fits into associated retail strategy. The Store-Category-Year level is achieved by collapsing weeks to years, while also collapsing all SKU’s to the category level. 794,731 observations are present in this version of the data.

Lastly, the Store-Year level is used to test H3: that the positive sales returns of a long tail brick-and-mortar retailing strategy are highest when the strategy is deployed consistently across all product categories. This level of aggregation is achieved by taking the previous Store-Category-Year level and collapsing further across categories to a store level view. This substantially reduces the number of observations to 26,810.

3.2. Variables

3.2.1. Dependent variables

The core dependent variable of interest is Dollars, which is measured as the total dollar sales for the focal SKU in the observation year. Two variations of this dependent variable are also considered for robustness: Adj. Dollars (the dollar sales adjusted for inflation to 2001 equivalents using the U.S. Consumer Price Index) and Market Share (the dollar sales of the focal SKU divided by the dollar sales of the product category in the same year).

3.2.2. Independent variables

Determining shifts in the long tail of the distribution over time is not a simple task and there is a clear tradeoff between alternative methodological approaches. The literature is indeed inconsistent on its use of relative versus absolute measures in determining the changes in the importance of the long tail. Relative measures (such as a Pareto split) to measuring sales growth (or decline) of the long tail move the slice point depending on how many products are offered: if a retailer opts to offer more products, it can end up artificially appearing as if those products in the real question is if less popular products begin to take sales from the bottom 80% of the sales distribution are selling less individually. Depending on how many products are offered: (a) the addition of more products to the category registering sales and/or (b) the growth in sales for individual products originally present at the tail end of the distribution.

The most pure solution is to instead measure product sales rank as a continuous variable ranging from highest to lowest, which avoids the concern of arbitrary slice points that may shift over time and alter the interpretation of the core results. Thus, Sales Rank is leveraged in this research as the key independent variable of interest in the core analysis. It is measured as the dollar sales rank of the focal SKU in the product category during the observation year, where the top selling SKU would be ranked as “1” and higher ranks correspond with lower sales amounts. Follow up analyses at the store level utilize both relative and absolute niche ratios in place of sales rank, to account for the level of aggregation deployed.

Sales rank is interacted with the Year to test H1: whether low selling products at the tail of the distribution are indeed growing their sales over time. Niche ratios and there associated interactions with year are used to test H2 and H3 in follow up analyses.

3.2.3. Control variables

Control variables are also considered in the empirical analysis. Grocery is the decimal percentage of sales that the focal SKU receives from the grocery (versus the drug) store channel during the observation year. Price is the average price per unit of sold volume. Feature is the decimal percentage of the SKU’s volume sold with in store print advertising feature support, while Display is the percent of volume sold with the support of a prime in store display shelf location.

Detailed variable descriptions (Table 1), descriptive statistics (Table 2), and pairwise correlations (Table 3) at the SKU-Category-Year level of the core analysis are provided next. Then the multi-layered approach to analyzing the data is walked through in the results section to follow. Model free evidence is considered first before proceeding to introduce regression analyses. Additional aggregation levels are also considered to extend the results further. All analyses were completed using STATA statistical analysis software.

4. Results

4.1. Growth of the long tail: Model free evidence (initial examination of H1)

Model free evidence of the growth of the long tail in the brick-and-mortar channel is reported first. To allow this analysis, the category level datasets were combined together retaining the sales rank for each SKU in each year-category combination. Data from 2002-2010 were then omitted and a percentage change in dollar sales from 2001 to 2011 for a certain sales rank level (i.e. #257) was calculated between these two endpoint years in the data. Lastly, the sales rank growth statistic was aggregated across five sales rank tiers of interest: #1, #2-#10, #11-#50, #51-#250, #251+. Fig. 1 therefore reports the cross-category average sales growth from 2001 to 2011 for sales ranks within each specified tier. A trend of growth in the long tail clearly emerges as top selling SKU’s are showing sales declines while less popular SKU’s are showing sales increases.

As it may be interesting to further consider how this growth may be different across the various categories in the data, Fig. 2 breaks this out by individual category. To allow for this presentation in a reasonably clean manner, a growth differential is calculated between sales tier #5 (products with sales rankings of #251 or worse) and sales tier #1 (the top selling product in the category). If this growth differential is positive, it means the products in the lowest tier grew faster on average than the

| Table 1 Variable descriptions. |
|-------------------------------|-----------------------|
| Variable          | Description                                    |
| Dollars           | Total national dollar sales for SKU during observation year |
| Adj. Dollars      | Dollar sales adjusted to 2001 equivalent using CPI   |
| Market Share      | Market share ($) for SKU during observation year |
| Sales Rank        | Sales rank ($) for SKU during observation year |
| Grocery           | Decimal percent of SKU’s $ sales from grocery channel |
| Price             | Average price per unit of SKU during observation year |
| Feature           | Decimal percent of SKU’s volume sales with feature support |
| Display           | Decimal percent of SKU’s volume sales with display support |
figures is that, while it is quite evident that sales growth of products in the long tail of the distribution are outpacing the sales growth of the most popular SKU’s, the relative Pareto Ratio is essentially incapable of empirically capturing this important development.

4.2. Model results to formally test long tail growth (H1)

Regression analyses (the first of which are reported in Table 4) are then conducted to more rigorously verify the already presented model free evidence. To achieve a robust set of final results to empirically cross-examine H1, three dependent variables are considered: raw sales (“Dollars”), CPI adjusted sales (“Adj. Dollars”), and the dollar sales based market share of the SKU (“Market Share”). Three model equations are therefore presented below, each with a distinct dependent variable to ensure robustness of the final results and associated conclusions. These analyses are conducted at the SKU-Category-Year level and include all 31 categories combined into a single analysis dataset. Following rigorous practice (Chintagunta et al., 2010), category specific effects are estimated to capture unobservable sources of heterogeneity, but are not reported to conserve manuscript space. The model equations are provided next, before moving on to report the associated results. Note that the subscripts used in these equations are: t (SKU), c (Category), and t (Year).

The empirical results (see Table 4) strongly support the model free evidence as there are positive and highly significant (p < .001) interaction effects between sales rank and year in all three model specifications. Thus, support for H1 is quite strong and robust across dependent variable choice.

4.3. Robustness check to confirm generalisability of core result (H1) to array of individual product categories

It should be noted here that the SKU-Category-Year regression analysis was run on each individual product category independently as well. This robustness check was conducted to confirm whether a wide or narrow range of product categories drives these results. The results indicate that the phenomenon is widespread. When dollars is the dependent variable of interest, the interaction between year and sales rank is positive and significant at the 0.05 level in 29 of 31 categories (null for hotdogs and negative for salty snacks). The results are positive and significant in all 31 categories when adj. dollars is the dependent variable of interest. Market share outcomes indicated positive and highly significant (p < .001) interaction effects between sales rank and year in all three model specifications. Thus, support for H1 is quite strong and robust across dependent variable choice.

4.4. Store-Category-Year level analysis to examine strategic role of the long tail in retail category assortments (H2)

While the prior results show that individual products in the long tail of the distribution are experiencing sales gains over time, it may not yet be clear whether it is strategically important for individual retailers to commit to stocking these products. The analysis to follow addresses this specific managerially relevant question.

A test as to how a retailer’s category level sales are impacted by the degree of focus on long tail product offerings is reported first. As was highlighted earlier, Brynjolfsson et al. (2010) have previously pointed
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out that whether absolute or relative cutoffs are used to identify niche offerings in the marketplace may impact results (with relative metrics being a more statistically harsh test). Results are reported here using each metric for purposes of robustness. A main effect (niche ratio) in the regression tests whether tilting a retailer’s strategic focus towards niche offerings is beneficial from a sales standpoint, while the interaction effect of niche ratio and year determines whether this hypothesized positive impact may be growing over time (H2).

These regressions include many of the same control variables (i.e., Grocery, Price, Feature, Display) as the previous regressions, albeit at a new level of aggregation (Store-Year-Category). Private Label is added here as a new control variable that is relevant at the store level as it considers the percentage of category sales accounted for by private label products. Also, while the previous analysis included category fixed effects, these regressions include both category fixed effects and market fixed effects. The model equations for these analyses are as follows (note that subscript s is used for stores).

(4) \[
\text{Dollars}_{st} = \alpha_0 + \beta_1 \text{Relative Niche Ratio}_{st} + \beta_2 \text{Year}_{st} + \\
\beta_3 \text{Relative Niche Ratio}_{st} \times \text{Year}_{st} + \beta_4 \text{Private Label}_{st} + \beta_5 \text{Grocery}_{st} + \\
\beta_6 \text{Price}_{st} + \beta_7 \text{Feature}_{st} + \beta_8 \text{Display}_{st} + \alpha_{st1} \text{Category}_{st} + \\
\alpha_{st2} \text{Market}_{st} + \epsilon_{st}
\]

(5) \[
\text{Dollars}_{st} = \alpha_0 + \beta_1 \text{Absolute Niche Ratio}_{st} + \beta_2 \text{Year}_{st} + \\
\beta_3 \text{Absolute Niche Ratio}_{st} \times \text{Year}_{st} + \beta_4 \text{Private Label}_{st} + \beta_5 \text{Grocery}_{st} + \\
\beta_6 \text{Price}_{st} + \beta_7 \text{Feature}_{st} + \beta_8 \text{Display}_{st} + \alpha_{st1} \text{Category}_{st} + \\
\alpha_{st2} \text{Market}_{st} + \epsilon_{st}
\]

These results, which do indeed support the growth of the strategic importance of the long tail over time, are reported in Table 5 to follow. Both the main effect for niche ratio and the interaction between niche ratio and year are positive and highly significant (p < .001) in both model specifications. Support for H2 is therefore claimed.

4.5. An analysis of the store level strategic implications of cross-category assortment planning strategy (H3)

Lastly, one may presume that a retailer’s commitment to a strategy of providing a wider variety of products across its various product categories may be important as it may be assumed that the long tail of products are often bought by a base of customers that consume niche offerings in numerous product categories. Thus, in Table 6, a final result is reported in which the data are aggregated one more step from the category-store-year to the store-year level.

Each control variable from the models reported in Table 5 is averaged during this aggregation. Dollar sales (the dependent variable) are summed across all categories. The count of categories served is added as an additional control variable to predict total store level sales. Lastly, the category level niche ratios were accounted for in terms of both the mean ratio and their standard deviation of observed ratios. This second metric, “niche variation”, will be higher when a retailer is less consistent in their strategy towards long tail products across the multiple product categories in their overall retailing assortment. It is expected that, holding the average niche ratio constant, a higher variation in niche strategy will be detrimental to sales and that this negative effect will be growing over time. Model equations are presented next before reporting the associated results.

(6) \[
\text{Dollars}_{st} = \alpha_0 + \beta_1 \text{Relative Niche Ratio}_{st} + \beta_2 \text{Year}_{st} + \\
\beta_3 \text{Relative Niche Ratio}_{st} \times \text{Year}_{st} + \beta_4 \text{Relative Niche Variation}_{st} + \\
\beta_5 \text{Private Label}_{st} + \beta_6 \text{Grocery}_{st} + \beta_7 \text{Price}_{st} + \beta_8 \text{Feature}_{st} + \beta_9 \text{Display}_{st} + \\
\beta_{10} \text{Categories}_{st} + \alpha_{st1} \text{Market}_{st} + \epsilon_{st}
\]
Dollars \[= \alpha_0 + \beta_1 \text{Absolute Niche Ratio}_t + \beta_2 \text{Year}_t + \beta_3 \text{Absolute Niche Variation}_t + \beta_4 \text{Private Label}_t + \beta_5 \text{Display}_t + \epsilon_t \]

The results, reported in Table 6 below, support this final assertion. This model specification reinforces the support for H2 at the overall store level, while adding empirical support for H3. In both specifications, the interaction between niche ratio and year is positive and significant, while the interaction between niche variation and year is negative and significant.
4.6. Summary of key findings

Products in the tail end of the sales distribution are experiencing greater sales growth over time when compared to more popular products. This phenomenon is occurring consistently across nearly all studied categories in the brick-and-mortar channel. From the perspective of individual retailers, a greater commitment to the stocking of products in the long tail leads to higher sales outcomes and this effect is growing over time. In addition, the sales returns to long tail strategy are highest for individual retailers, a greater commitment to the stocking of products in most product categories studied.

5. Discussion

5.1. General discussion

This research seeks to fill a discrete gap in the literature by asking the following fundamental question: is long tail theory becoming increasingly applicable to the brick-and-mortar channel for consumer-packaged goods (CPG’s)? Or, in other words, are the strategic roles of hit and niche products evolving over time in this channel? To do so, it builds upon and extends these recent prominent papers in the area (most notably: Kim et al., 2017 and Tanusondjaja et al., 2018) by arguing that fundamental shifts in how consumers shop and make decisions in brick-and-mortar retail settings (Huang et al., 2009; Lamberton and Stephen, 2016; Shankar et al., 2016; Wang et al., 2015) are altering the applicability of category dynamics: it should be noted here that a similar assertion was made previously by Brynjolfsson et al. (2010). These metrics confound two distinct empirical questions when it comes to long tail research: (a) if the size of the assortment changing over time, and (b) if the class of less popular products is accounting for a greater share of total sales. When the variety of products available in a market expands, the Pareto Ratio somewhat arbitrarily shifts the breakpoint of hit versus niche products further down the sales rank list. This can lead to an apparent increase in the share of market sales commanded by hit products without acknowledging the fact that (a) a greater number of products in the market are registering some sales and (b) the consolidated list of top selling products from the previous time period has likely forfeited some of its sales to mid- and low-popularity products. This has substantial methodological implications for future research, since competing Pareto rule methodologies have been used in the literature to date. Our extant base of theoretical knowledge in this area should be reconsidered, given these revelations about how crucial methodological approach is for the nature of derived empirical results.

The final theoretical contribution is a broader one. This study contributes further empirical evidence that marketing environment shifts can substantially alter consumer search and decisions processes on a permanent basis. Sarmiento et al. (2019) recently showed that economic recessions serve to reshape consumer preferences over the long-term. Evolution in consumer capabilities and tendencies to engage in information search with mobile technologies during brick-and-mortar shopping trips further indicate that fundamental shifts are on the horizon for retailers. This builds on similar sentiments expressed by other authors in this area (Baier and Stüber, 2010; Pantano and Vannucci, 2019; Paul and Rosenbaum, 2020), and it clearly extends to inquiries that are broader and behaviors of consumers in relation to mobile technologies (Shankar et al., 2016; Wang et al., 2015), it is posited here that this second condition increasingly applies to the brick-and-mortar channel as well. Thus, while it is unlikely that long tail strategy will ever be as pronounced in the brick-and-mortar channel (supply side issues are still present after all), this paper posits that the evolution of consumer search may be making a long tail brick-and-mortar strategy increasingly viable over time. The empirical evidence substantiates these claims.

It is crucial to emphasize that this study only examines data until the end of 2011: the estimates of the use of mobile technology by brick-and-mortar shoppers to easily find out about less popular product offerings in real time are likely much lower during the period of this study than they are today. It is thus likely that the presented results are but a conservative estimate of the strategic value niche products in the long tail of the sales distribution may pose for the brick-and-mortar channel. One may intuitively expect that increasing use, and even full scale reliance on, mobile technologies for information to power consumer decisions is only further growing the importance of expanding category assortment product breadth for brick-and-mortar retailers.

5.2. Theoretical contributions

The first major contribution to this study is that long tail theory appears to be increasingly applicable to the brick-and-mortar channel. Long assumed to be incompatible with traditional retailing contexts (Brynjolfsson et al., 2011; Kim et al., 2017), a shift in consumer technological capabilities and behaviors (Huang et al., 2009; Lamberton and Stephen, 2016) has led to an increased importance of less popular SKU’s in brick-and-mortar retail assortments. This finding challenges the underlying assumption that consumer search is considerably less costly in the online context than in the brick-and-mortar context. Perhaps a gap in the relevance of niche products still exists between the online and brick-and-mortar retail channels, but the margin of this gap has closed substantially. Long tail theory should be revisited in regards to its applicability to online and offline channels accordingly.

Another key academic takeaway is that the use of common relative metrics like the Pareto Ratio is potentially damaging for understanding category dynamics: it should be noted here that a similar assertion was made previously by Brynjolfsson et al. (2010). These metrics confound two distinct empirical questions when it comes to long tail research: (a) if the size of the assortment changing over time, and (b) if the class of less popular products is accounting for a greater share of total sales. When the variety of products available in a market expands, the Pareto Ratio somewhat arbitrarily shifts the breakpoint of hit versus niche products further down the sales rank list. This can lead to an apparent increase in the share of market sales commanded by hit products without acknowledging the fact that (a) a greater number of products in the market are registering some sales and (b) the consolidated list of top selling products from the previous time period has likely forfeited some of its sales to mid- and low-popularity products. This has substantial methodological implications for future research, since competing Pareto rule methodologies have been used in the literature to date. Our extant base of theoretical knowledge in this area should be reconsidered, given these revelations about how crucial methodological approach is for the nature of derived empirical results.

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Table 6

| DV Dollars | Niche Ratio Relative Dollars | Niche Ratio Absolute Dollars |
|-----------|-----------------------------|-----------------------------|
| 26,810 | 9,169,100 | 12,610,900 |
| 26,810 | 9,169,100 | 12,610,900 |
| 60 | 60 | 60 |
| 60 | 60 | 60 |

Wald chi²

Niche Ratio

-2,742,587.00 ***

9,169,100.00 ***

6838.33 ***

Niche Ratio

-1,843,915.00 ***

12,610,900.00 ***

7983.93 ***

Year

-166,792.50 ***

24,938.85 **

2,742,587.00 ***

Niche Ratio (x) Year

547,931.10 ***

-4,201,647.00 ***

258,057.60 *

Niche Variation

2,195,594.00 ***

-272,070.70 *

258,057.60 *

Display

Niche Variation (x) Year

-69,924.20 *

-64,095.30 ***

272,070.70 *

Private Label

-4,609,506.00 ***

-1,930,605.00 ***

2,284,051.00 ***

Grocery

13,650.14 (8496.63)

284,054.20

6,721.80 (5471.02)

Price

-13,650.14 (8496.63)

2,284,051.00 ***

feature

25,389.93 ** (8551.01)

284,054.20

-272,070.70 *

Display

2,227,102.00 ***

125,291.00 *

1,930,605.00 ***

Categories

57,910.94 *** (5471.02)

58,655.72 *** (5376.95)

Table 6: Regression results; Store-Year level of analysis; Market effects estimated but not reported; *p < .1, **p < .05, ***p < .01, +++p < .001.
than just retail strategy decisions of category assortment and the relative roles of hit and niche products within a given product category.

5.3. Managerial implications

The most direct and perhaps obvious managerial implication of this research is that brick-and-mortar retailers must consider a wider variety of products to include in their assortment planning activities. Simple traditional rules like the Pareto approach to assortment planning may no longer apply. Retail managers should also consider whether information flow for consumers has now reached a point of capacity or if it is likely to continue growing: this determination will help the brick-and-mortar channel determine if niche products in the long tail of the sales distribution are poised to grow even more important in coming years or if their potential have instead been achieved at this point.

Previous empirical findings demonstrated that significant variation in brick-and-mortar retail sales exist within the same product category across geographic sub-regions of the same country. Bronnenberg et al. (2007) demonstrated this in the United States, while Ataman et al. (2007) did so in France. The findings within the current study add additional nuance for retail managers to consider in category assortment planning decisions: both spatial and temporal dynamics should be accounted for. The roles of certain brands and products within a product category are likely to be different across geographical sub-regions at any given time and are likely to shift and evolve over time in response to environmental factors such as consumer search capabilities and processes. Investments in retail analytics (Albors-Garrigos, 2020; Kim and Song, 2020; Moiseeva and Timmermans, 2016; Mulcahy and Riedel, 2020) could be a viable way to strategically account for both spatial and temporal dynamics successfully.

Retail managers should take heed that, while consumers report a general preference for wider product assortments (Kahn and Wansink, 2004), they can become overwhelmed at time of decision-making if too many options are presented (Broniarczyk and Griffin, 2014; Iyengar and Lepper, 2000). Strategies to present products on the shelves in strategic manners to promote fluency and ease of processing have the potential to maximize positive sentiments of category variety perceptions without overwhelming consumers (Deng et al., 2016; Townsend and Kahn, 2014). With widening sales distributions by product category, retailers that best adapt by offering more category variety and presenting that variety effectively to consumers should enjoy a competitive advantage in the marketplace.

6. Conclusion

6.1. Limitations and future research

There are some limitations to this study, which provide opportunity for future research advances. While this study focuses on revenue, indicating important demand side outcomes, further research could incorporate cost-side information to determine whether a similar profitability impact exists. Strategic orientations of particular retailers (Brusch et al., 2019) and their associated strategic fit with offering products in the long tail could be a particularly interesting avenue to investigate. Additional research could also consider new product categories or could perform analyses at different levels of aggregation to add nuance to the current findings. Investigations into particular product type subsets that are likely to be present in the long tail of the sales distribution such as organic (Koнак, 2018), environmentally friendly (Wei et al., 2018), specialty (Calvo-Forral and Lévy-Mangin, 2016), and local (Yildiz et al., 2018) products would be warranted. Another interesting line of inquiry could be the impact of individual shopper characteristics and behaviors, perhaps centering on individual consumer decision processes and transactional events. In particular, the novel Coronavirus has significantly influenced shopping behaviors by shortening customers’ visiting time in stores, which may impact the relationships studied here. More stable consumer characteristics such as generational cohort membership (Phua et al., 2020) and socioeconomic status (White and Tong, 2019) should also be considered in future consumer level inquiries. Continuing to update our empirical understanding of the long tail phenomenon in brick-and-mortar and online channels would be useful to track potential future evolutions.

6.2. Concluding remarks

In broader terms, the findings of this research indicate that changing capabilities and behaviors of consumers due to technological advances are changing the landscape of brick-and-mortar retailing. These findings contribute to a growing perspective in the literature that retailing is being transformed by changing environmental conditions (Baier and Stüber, 2010; Paul and Rosenbaum, 2020) and that brick-and-mortar retailers are particularly affected (Azeem et al., 2019; Badrinarayanan and Becerra, 2019; Helm et al., 2020). Category assortment variety decisions should be particularly revisited as the findings of this study directly indicate. As more information flows occur, brick-and-mortar retail customer markets are becoming more likely to demand a wider variety of product offerings. One also may posit that the faster communication and flow of information could lead to higher demand for new product and brand offerings, shortening product life cycles, and necessitating more frequent updating of assortments by brick-and-mortar retailers. What is most definitely clear is that consumers are adapting and brick-and-mortar retailers must strategically adapt as well to remain competitive.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2020.102234.

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