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Modeling Total Distribution Velocity

Abstract

For retailers and suppliers, keeping track of distribution velocity, which refers to the market-share gains per additional point of distribution, is important to assess the performance of their products in a market. Common distribution-velocity models use distribution-breadth metrics. However, distribution-breadth metrics lack the variability needed to meaningfully differentiate competing brands. This article presents a new approach for modeling distribution-velocity using weighted total distribution, which combines distribution-breadth and distribution-depth. Using retail scanner data from the U.S. market covering a total of 1,682 brands in 12,049 stores across five channel types, we propose total-distribution models that are easier to specify, better reveal the differences in distribution between brands, and thus improve competitive benchmarking. This novel modeling approach based on total distribution serves as a pivotal contribution by providing an effective analytical tool for competitive benchmarking in diverse market environments. It allows brands to increase their market-share by spending on a fair share of total distribution. These findings highlight the usefulness of a total-distribution metric as a measure of competitive distribution coverage to support product-portfolio and category-management decisions.

Keywords: total distribution; distribution velocity; CPG; category management

Modeling Total Distribution Velocity

1. Introduction

To succeed in the challenge of making their products available to potential buyers, firms require effective distribution systems and adequate management of those systems (Farris, 2004; Farris et al., 2016). Multiple studies have identified retail distribution as a critical driver of brand performance. Indeed, distribution plays an important role in generating growth and building market potential for new brands (Ataman et al., 2008). Compared to advertising or promotion, spending on distribution has a stronger impact on sales performance (Ataman et al., 2008; Ataman et al., 2010; Srinivasan et al., 2010).

Distribution has two main dimensions: breadth and depth. Whereas distribution breadth indicates how easy it is to find a brand's product *across* sales outlets within a market, distribution depth considers the brand's availability *within* a sales outlet (Ailawadi & Farris, 2017, 2020; Farris et al., 1989). Effectively managing both dimensions of distribution and deciding how much and what type of distribution coverage is needed are critical tasks in marketing management.

Within the stream of literature analyzing the relationship between distribution and market share (known as distribution velocity), the primary focus has been on distribution breadth (Ailawadi & Farris, 2020; Farris et al., 1989; Hirche et al., 2021a; Reibstein & Farris, 1995; Wilbur & Farris, 2014). However, in retail practice, distribution breadth only provides a one-sided story. The additional measurement of distribution depth is critical for benchmarking and competitive analysis. Competition between brands increasingly manifests as obtaining scarce shelf space (Martinez-de-Albeniz & Roels, 2011; Murray et al., 2010; Venkatesan et al., 2015). Although new manufacturers enter markets and the variety of products in categories continuously increases, the shelf space available in retail stores remains limited (Murray et al., 2010). Therefore, to prevent competitive disadvantage, monitoring a brand's availability not only in its market but also within each store is vital (Venkatesan et al., 2015).

So far, only a few studies have applied a more comprehensive approach to measure distribution by including distribution depth into the analysis (Ataman et al., 2008; Datta, 2017; Kruger & Harper, 2006; Slotegraaf et al., 2003). For example, Slotegraaf et al. (2003) use a total-distribution metric, among other variables, in their multiple regression analyses to investigate the influence of firm resources on the success of marketing actions. Kruger & Harper (2006) explore ways to incorporate distribution depth in modeling the relationship between distribution breadth and market share by considering "items per store." Ataman et al. (2008) consider distribution breadth and depth as separate variables in their diffusion models. Datta et al. (2017) use a total-distribution metric in their regression models to estimate market-share elasticities. However, an empirical investigation of distribution velocity that combines both distribution breadth and depth is lacking in the literature—an important gap that this paper aims to fill.

From an analytical viewpoint, distribution velocity based on distribution breadth presents a convex and increasing curve pattern for the majority of product categories (Kruger & Harper, 2006; Wilbur & Farris, 2014). This poses analytical challenges for benchmarking tasks, because large brands tend to reach high distribution levels with low variability of measured distribution across brands (Michis, 2023). The brands with the highest market shares have very similar distribution breadth, which makes meaningful comparisons almost impossible.

A distribution metric that addresses these analytical challenges and helps fill the research gap described above but has received little attention so far is *total distribution*. By combining distribution breadth and depth, a total-distribution metric enables managers to assess the availability of a brand’s whole product portfolio in a market. Considering that product categories are constantly growing in their number of stock-keeping units (SKUs), this metric provides important insights for marketers. Distribution-velocity models based on total distribution can quantify category trends and indicate the success of distribution decisions with regard to market share (Ailawadi & Farris, 2020). Using a more comprehensive distribution metric when modeling distribution velocity increases diagnostic ability and estimation accuracy compared to common distribution-velocity models based on distribution breadth (Ailawadi & Farris, 2017; Farris, 2004; Kruger & Harper, 2006). Furthermore, a possible linear curve pattern of distribution velocity based on total distribution (Ailawadi & Farris, 2020) may facilitate the use of simpler model specifications. Finally, especially for brands with high levels of distribution coverage, extending the distribution-velocity model via distribution depth increases the variability of the distribution measure, which improves the comparability between brands. These mentioned features of distribution velocity can help identify strategic opportunities that remain unseen with common distribution-breadth metrics (Kruger & Harper, 2006).

Against this background, this article makes two contributions to the literature. First, we provide empirical evidence that a total-distribution metric offers substantive benefits for analyzing and interpreting distribution velocity. Second, we systematically compare different models for distribution velocity (based on total distribution) to guide managers when applying distribution-velocity models for a given situation.

To develop distribution-velocity models that describe the relationship between total distribution and market share, this study uses sales data on 10 consumer packaged goods (CPG) categories from the U.S. market in 2019. We estimate and evaluate a variety of model types to identify those models that accurately describe the distribution velocity in the data. Prior literature has suggested the relationship between total distribution and market share to be linear and increasing (Ailawadi & Farris, 2020). Based on this notion, the aim of this work is, first, to validate whether the relationship between total distribution and market share indeed follows a linear curve pattern and, second, to identify the model type that best fits the data. Marketing practitioners and researchers can use the findings to develop suitable distribution-velocity models for benchmarking and competitive analysis based on the relationship between total distribution and market share.

To this point, distribution-velocity models that account for both dimensions of distribution have yet to be established. This work contributes to filling this gap by being the first study to systematically analyze the relationship between total distribution and market share by developing and empirically estimating distribution-velocity models that consider both distribution breadth and depth to measure distribution coverage. Thereby, we extend the analysis of the relationship between distribution and market share with a total-distribution metric and new distribution-velocity models that provide a more granular picture of a brand's distribution coverage. These distribution-velocity models estimate expected market outcomes as a function of a brand's total distribution and provide important insights into a market's competitive distribution structure. They also reveal whether brands' current distribution levels are likely to sustain over time (Ailawadi & Farris, 2020).

2 Theoretical background

In the following sections, we briefly describe the foundations and recent advances in the literature on the relationship between distribution and market share. We point out essential metrics for building distribution-velocity models.

2.1 The relationship between distribution and market share

Distribution has two main dimensions: breadth and depth (Ailawadi & Farris, 2020). Distribution breadth refers to the intensity of market coverage, indicating how easy it is for consumers to find a brand (or a brand's products). A brand can be easy to find either because of its availability across many stores or because the brand is stocked in the most important stores in terms of customer traffic. Distribution depth refers to a dimension of distribution within a store. According to Ailawadi & Farris (2020), it indicates a brand's attractiveness and competitive position inside the store. Distribution breadth influences distribution depth and vice versa. Brands widely distributed in a market gain more attention from resellers, and their listing decisions affects distribution depth due to competition with other resellers. However, too much breadth can lead to intense price competition, resulting in lower margins and making the brand less attractive to resellers, which can reduce resellers' motivation to invest in depth. In addition, extending the depth of a product category can improve resellers' overall category sales and therefore affect distribution-breadth metrics that focus on category importance (Ailawadi & Farris, 2017, 2020). Together, distribution breadth and depth drive market performance.

With the emergence of new retail channels and increasing competition for scarce shelf space, proper assessment of the relationship between distribution and market performance is becoming more important (Farris et al., 1989; Venkatesan et al., 2015). A robust finding in this area is that of a convex curve pattern for the relationship between distribution breadth and market share (Farris et al., 1989; Hirche et al., 2021a; Kruger & Harper, 2006; Wilbur & Farris, 2014). This convex curve pattern describes a "double jeopardy" phenomenon, whereby high-share brands tend to sell more per point of distribution (Friberg & Sanctuary, 2017; Kucuk, 2008; Wilbur & Farris, 2014). Double jeopardy patterns are also valid with regards to other metrics (e.g., penetration rate, purchase frequency, share of requirements) in relation to market share (Jung et al., 2016).

Moreover, distribution is both a driver and a result of market performance (Farris et al., 1989)[1]. Brands with high market shares tend to have more loyal customers who choose stores that stock their preferred brands (Wilbur & Farris, 2014), which in turn results in stronger demand by retailers and better shelf space (Farris, 2004; Farris et al., 1989). In addition, retailers with limited assortments tend to stock market-leading brands to avoid losing customer traffic, which means that brands enter less competitive environments as their market shares increase (Farris et al., 1989).

The primary purpose of modeling distribution velocity is to identify appropriate distribution levels given specific market-share goals (Ailawadi & Farris, 2020; Wilbur & Farris, 2014). Reibstein & Farris (1995) propose a parametric model to estimate market share based on distribution breadth. The model can adapt to different curve patterns in data due to its flexibility, making it a useful approach for analyzing different product categories. Kruger & Harper (2006) revalidate this model and extend it to include product-line availability by including items per store. Wilbur & Farris (2014) develop different quadratic models, adjusting the curve pattern with respect to brand- and category-specific characteristics. They use both brand- and SKU-level data, arguing that most marketing decisions, such as go-to-market strategies or discontinuations, are made at the SKU level. Their findings support the previously identified increasing convex relationship. However, besides Kruger & Harper's (2006) initial exploratory approach to incorporate distribution depth into distribution-velocity models, no study thus far has taken a

[1] Note that models of the relationship between distribution and market share (distribution-velocity models) do not reflect a causal relationship. Therefore, the primary purpose of modeling the relationship is to estimate a pattern in a given market, which can then be used as a basis for comparative analyses, such as comparing markets and product categories, or benchmarking brands and SKUs (see, e.g., Ailawadi & Farris 2020; Hirche et al., 2021a & 2021b).

systematic approach to modeling distribution velocity in relation to market share based on total distribution.

2.2 Distribution-breadth metrics

Non-weighted distribution-breadth metrics measure the absolute number of stores carrying a brand (Ailawadi & Farris, 2020). The most common non-weighted metric is numeric distribution (Ailawadi & Farris, 2017), calculated as the number of stores that stock the brand divided by the number of stores in the focal market (Farris et al., 2016). Numeric distribution does not take into account the different sales volumes of individual stores and is therefore suitable for markets with low concentration, where a substantial share of sales is generated in smaller stores (Borin et al., 1991; Guissoni et al., 2020).

Weighted-distribution metrics consider the importance of individual stores in relation to other stores in a market (Farris et al., 2016) and therefore provide a more accurate picture of distribution coverage (Venkatesan et al., 2015). Stores carrying a brand are weighted according to the sales revenue they generate, which is particularly important in markets in which customer traffic differs to a great extent (Farris et al., 2016). The most commonly used weighted metrics are "all commodity volume" (ACV) and "product category volume" (PCV) (Ailawadi & Farris, 2017; Reibstein & Farris, 1995). Both metrics can be expressed either as a dollar value, describing a store's total sales volume, or as a percentage, representing a store's sales volume relative to the sales volumes of other stores in the market. While ACV is weighted by total store sales, PCV is only weighted by stores sales of the product category in question (Ailawadi & Farris, 2017, 2020; Farris et al., 2016). For most mainstream CPG products, ACV and PCV provide a similar picture because a store's share of all commodity sales is usually close to a store's share of the specific category sales. ACV and PCV differ if a large portion of a CPG's category sales are generated in specialty stores. In this case, the share of category sales is higher than the share of all commodity sales for these specialty stores (Farris et al., 1989). For a new brand in a growing category, ACV provides a better picture of distribution coverage because the distribution of the category has not yet reached its full potential. Therefore, its current size is not a valid measure to evaluate the brand's sales potential. With growing competition, PCV becomes more relevant since companies should begin focusing on their shares in the category rather than the whole market (Ailawadi & Farris, 2020).

When assessing distribution-breadth metrics at the brand level, a store is included if at least one SKU of its product line is stocked (Ailawadi & Farris, 2017). Therefore, large brands tend to reach high distribution levels with low variability of measured distribution across brands. As for most categories, it is rarely sufficient to have only one SKU on the shelf. Monitoring distribution breadth only can thus lead to a lack of important information, such as the impact of line extensions on a brand's performance (Aurier & Mejía, 2020).

2.3 Distribution-depth metrics

Diverse definitions and descriptions of distribution depth can be found in the literature. Distribution-depth metrics focus on a brand's representation at the point of purchase. This can be either in terms of how prominently a product is promoted, to what extent the product line of the supplier is stocked, or how well the reseller supports a customer's path-to-purchase (Ailawadi & Farris, 2017, 2020).

One approach to measuring the impact of distribution depth on brand performance is by measuring shelf-space elasticity. Shelf-space elasticity describes the ratio of additional sales to additional space allocated in a store (Eisend, 2014). As shelf space increases, so does the likelihood that a brand will be noticed by customers (Eisend, 2014). The number of shelf facings positively influences visual attention and brand evaluation (Desmet & Renaudin, 1998; Drèze et al., 1994). Doubling the number of shelf facings can increase brand choice by up to 67% (Chandon et al., 2009). However, the number of shelf facings may consist of multiple items of the same SKU and are therefore not suitable metrics to assess which part of a brand's product portfolio is in stock. The latter can be assessed by a brand's number of SKUs per store, which is an important determinant of the brand's sales volume and long-term market potential—even more important than advertising and price discounts (Ataman et al., 2008)[2].

However, it is not possible to get a complete picture of a brand's distribution by examining only the breadth or only the depth of distribution. Ideally, both concepts should be taken into account to establish a combined metric (Ailawadi & Farris, 2020).

2.4 Combining breadth and depth to total distribution

In most product categories, it is crucial for a brand to have multiple SKUs on the shelf. When evaluating the availability of a brand's products, standard distribution-breadth metrics, such as ACV or PCV, are rarely sufficient because they only reflect distribution coverage across stores and ignore the depth of availability within stores. A total-distribution metric assesses the extent to which a product line is in distribution as opposed to measuring only whether a single product of a brand is available. A brand's total distribution uses the weighted distribution-breadth metric (ACV or PCV) and multiplies it with the number of SKUs the brand has in stock at individual stores. The metric is calculated either as the sum of all weighted total-distribution percentage points or as the share of total distribution relative to other brands in the category. While the sum of all weighted total-distribution percentage points will increase over time with each additional

[2] In this paper, "distribution depth" is defined as the extent of market penetration achieved by a product, measured by its presence across retail stores. In line with this definition, we operationalize "distribution depth" as the number of SKUs of a brand per store and integrate it into the respective metrics (see Equation 10).

SKU distributed in the market, the share of total distribution will only increase if the growth of a brand's distribution exceeds the growth of the number of SKUs within the category. Therefore, calculating a brand's total distribution relative to the market's cumulated total distribution is useful to evaluate market growth (Ailawadi & Farris, 2020).

A total-distribution metric has higher variability than common distribution-breadth metrics, such as ACV or PCV. The latter do not take into account changes in the availability of product portfolios within stores. Stocking or delisting additional SKUs of a brand does not change the brand's ACV or PCV. This is a particularly important limitation of conventional distribution-breadth metrics as the decision to remove a whole brand from a store's assortment entirely is a much more significant hurdle for a category manager than removing individual SKUs of a brand. An increase (decrease) of total distribution often means additional listings (delistings) of SKUs in a store that already stocks similar products of a brand. In contrast, increases (decreases) in PCV or ACV always refer to stores that are completely new outlets for a brand (that have eliminated the entire brand) (Datta et al., 2016). A combined measurement leads to substantially higher market-share deviations from expected distribution velocity (Ailawadi & Farris, 2020). Due to this increased variability, modeling distribution velocity based on total distribution improves diagnostic ability at the brand level (Ailawadi & Farris, 2017, 2020; Kruger & Harper, 2006).

"Fair share of distribution" refers to the idea that a brand's market share should equal its share of total distribution relative to other brands in the focal category (Nielsen IQ, 2020; Simon, 2013). A brand that is below its fair share might try to negotiate additional shelf space given its share of sales revenue. In contrast, a brand that is above its fair share should be cautious about putting too much emphasis on negotiating shelf space. Modeling the relationship between total distribution (as a brand's share relative to other brands in the category) and market share can help assess whether positions above or below the fair share of distribution are actually unjustified or whether these deviations are to be expected in some cases. Previous studies on the relationship between market share and distribution breadth shows low share brands suffer twice (double jeopardy). They not only sell less, but also less than their fair share of distribution as the relationship is not linear. This result implies that, in order to become a high share brand, a low share brand needs to obtain more than their fair share of distribution (e.g. 70% distribution breadth to get 50% market share). However, for the relationship between market share and total distribution, Ailawadi & Farris (2020) hypothesize that this relationship is linear. If this hypothesis is confirmed, it implies that in order to grow, a low share brand just needs to obtain a fair share of total distribution (e.g. 50% total distribution to get 50% market share). This is particularly important for brand managers to know as buying distribution is costly. If the relationship is linear, that could help brand managers avoid over-spending on distribution. Therefore, modeling the relationship between share of total distribution and market share and evaluating the curve pattern of this relationship provides useful insights into the concept of a brand's fair share of distribution.

3 Data

We use syndicated retail-scanner data from the U.S. market provided by the Nielsen Company (US), LLC and the Kilts Marketing Data Center at the University of Chicago Booth School of Business.[3] The transaction files include information about weekly pricing, sales volume, and merchandising conditions of participating stores over a one-year period (2019).

[3] Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer, LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The

In line with previous research on the relationship between distribution and market share (e.g., Wilbur & Farris, 2014), we exclude private labels from the analysis. Their distribution is controlled by the retail chain that owns the private label, and private labels are generally not sold in stores owned by competing retailers. As a consequence, private labels often have substantially higher market shares per point of distribution compared to national brands (Farris, 2004).

We focus on products that were in distribution during the entire observation period. We filter for SKU-store combinations with at least one registered sale in the first (Q1) and the last quarter (Q4) of the observation period[4]. Weekly store PCV values are assigned to all SKUs in the sample even if they have no registered sale in a certain week.[5] The data covers the US states of California, Texas, New York, and Wisconsin and a total of 12,049 stores (Texas: 4,549; California: 4,540; New York: 2,231; Wisconsin: 729) across five different channel types. Table 1 provides summary statistics.

[insert Table 1 here]

The data covers various food and non-food CPGs (Table 2). All categories were available throughout the year, which limits potential seasonality effects. In total, the categories yielded a total of $7,313 million in 2019.

[insert Table 2 here]

The data includes 9,624 SKUs divided into 1,682 brands, resulting in an average of 5.72 SKUs per brand. The category "ground and whole bean coffee" contains the most brands (401)

University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[4] In our analysis, we assume that each SKU is listed throughout the entire year to maintain consistency and simplify the computational process across time frames. This assumption aligns with common industry practices, particularly in the consumer-packaged goods sector, where significant brand SKUs are generally negotiated for shelf placement on an annual basis, ignoring individual SKUs that are only listed temporarily.

[5] This operationalization reduces potential built-in biases regarding the actual availability of SKUs in stores during times when no sale is recorded.

and SKUs (2,891), the category “facial tissues” has the fewest brands (43), and the category “dental floss” has the fewest SKUs (142). The mean market share of the market-leading brands is 26.36%. The large difference between the median and maximum market shares also shows that the majority of brands within a category are clustered at the lower end of the market-share scale, while a small number of brands account for most of the category revenues.

The mean of the maximum share of PCV-weighted total distribution is 19.57%. Comparing maximum market share and maximum share of PCV-weighted total distribution, market-leading brands are, on average, below their fair share of distribution according to the previously described definition. Brands may appear to have strong distribution coverage based on their PCV levels; however, applying a total-distribution metric might reveal that a brand is not performing as expected.

4 Method

4.1 Market-performance metrics

In the following, we specify and explain all important metrics required to derive the final metrics for modeling distribution velocity based on total distribution. This helps to ensure that the operationalization of the metrics is transparent and reproducible. We calculate average weekly sales revenues and market shares on the category and store levels for the observation period. Using weekly averages has the advantage that it accounts for shifts in the market structure during the year and adjusts for potential seasonal effects (Basuroy et al., 2001; Neslin, 1990). We follow a stepwise calculation of measures, leading to the average weekly market share.

Weekly store sales revenue per category. The variable $Sales_{scw}$ refers to the sales revenues of store s in category c in week w. This metric results from multiplying the units of each store, category, and week combination with the respective price and then dividing by the metric price multiplier variable $Prmult_{scw}$, which reflects special offers, such as "two for one."

$$Sales_{scw} = Units_{scw} \times \frac{Price_{scw}}{Prmult_{scw}} \tag{1}$$

Total weekly category/store sales revenue. The total weekly store sales revenue, denoted as $Sales_{sw}$, is calculated as the sum of sales revenues in all categories *c* in store *s* in week *w*. Similarly, the total weekly category sales revenue, $Sales_{cw}$, is calculated as the sum of sales revenues of all stores generated by category *c* in week *w*. The total weekly store sales revenue is later used to calculate the PCV shares of individual stores. The total weekly category sales revenue is used for market-share calculations.

$$Sales_{sw} = \sum_{c=1}^{C} Sales_{scw} \tag{2}$$

$$Sales_{cw} = \sum_{s=1}^{S} Sales_{scw} \tag{3}$$

Brand sales revenue. To calculate brand market shares in each category, we need individual brand sales revenues. The variable $Sales_{bcw}$ refers to the sales revenues of brand *b* in category *c* in week *w*. It is calculated by summing up the sales revenue of each SKU *i* that belongs to brand *b* in each store *s* for category *c* in week *w*. The dummy variable Q_{iscw} takes the value of 1 if the SKU *i* belongs to brand *b* and 0 otherwise.

$$Sales_{bcw} = \sum_{s=1}^{S} \sum_{i=1}^{I} Q_{iscw} Sales_{iscw} \tag{4}$$

Weekly market share. The market share of brand *b* in category *c* in week *w* is calculated as the sales revenue of brand *b* in category *c* in week *w* divided by the sum of the sales revenues of all brands *b* (= 1, …, B) in category *c* in week *w*.

$$\%MS_{bcw} = \frac{Sales_{bcw}}{\sum_{b=1}^{B} Sales_{cw}} \tag{5}$$

Average weekly market share. Finally, one of the two metrics needed for distribution-velocity modeling is the average weekly market share of each brand. The average weekly market share of brand *b* in category *c* in the observation year (i.e., 2019)[6] is calculated by dividing the sum of weekly market shares $\%MS_{bcw}$ by 52.

$$\%MS_{bc} = \frac{\sum_{w=1}^{52} \%MS_{bcw}}{52} \quad (6)$$

4.2 Distribution metrics

We use PCV as the basis for our total-distribution metric because the product categories in our data are all mature in terms of category growth. While ACV tends to be more useful in growing product categories because the sales potential could exceed the current size of the category, PCV better reflects distribution coverage in established categories (Ailawadi & Farris, 2017). We calculate a brand's PCV as follows. First, the weekly store PCV share (equation 7) is calculated as the weekly sales-revenue share of a given store in the focal category. This value is then averaged over all weeks of a year (equation 8). Second, store PCV shares are assigned to each brand sold in that store in the respective week (equation 9) to subsequently obtain the average weekly brand PCV for the year (equation 10). The share of PCV-weighted total distribution (equation 12) is the final metric used for distribution-velocity modeling and is based on the PCV-weighted total-distribution points (equation 11).

Weekly store PCV. The weekly store PCV coverage, $\%PCV_{scw}$, is calculated by dividing the sales revenues of store *s* in category *c* in week *w* by the sales revenues of all stores *S* in category *c* generated in week *w*.

$$\%PCV_{scw} = \frac{Sales_{scw}}{\sum_{s=1}^{S} Sales_{cw}} \quad (7)$$

Average weekly store PCV. The average weekly store PCV is calculated by dividing the sum of all weekly store PCV values for the year by 52.

[6] Note that the observation year is not indexed in the formulas, since we analyze observations from one year (2019).

$$\%PCV_{sc} = \frac{\sum_{w=1}^{52} \%PCV_{scw}}{52} \quad (8)$$

Weekly brand PCV. The variable $\%PCV_{bcw}$ denotes the PCV value of brand *b* in category *c* in week *w*. It is calculated by summing up the PCV values of category *c* of all stores *s* (= 1, … *S*) that sold brand *b* in week *w*. Q_{bsw} is a dummy variable that indicates if brand *b* was sold in store *s* in week *w* (value 1) or not (value 0).

$$\%PCV_{bcw} = \sum_{s=1}^{S} Q_{bsw} \times \%PCV_{scw} \quad (9)$$

Average weekly brand PCV. Again, the weekly averages for the year are calculated by dividing the sum of all weekly brand PCV values by 52.

$$\%PCV_{bc} = \frac{\sum_{w=1}^{52} \%PCV_{bcw}}{52} \quad (10)$$

PCV-weighted total distribution. The PCV-weighted total distribution of brand *b* in category *c* is calculated by multiplying the average weekly store PCV for the year, $\%PCV_{sc}$, with the number of SKUs of brand *b* in store *s* in category *c*, i_{bsc}, (based on the assumption that all SKUs are listed throughout the entire year) and then aggregating this value over all stores *s* (= 1, … *S*). Note that i_{bsc} is a count variable that returns the number of SKUs and takes the value of 0 if store *s* did not list any SKUs of brand *b*, hence including only stores that stocked that brand in the calculation.

$$TDPCV_{bc} = \sum_{s=1}^{S} \%PCV_{sc} \times i_{bsc} \quad (11)$$

Share of PCV-weighted total distribution. The share of PCV-weighted total distribution of brand *b* in category *c* is calculated as the PCV-weighted total distribution of brand *b* in category *c* divided by the sum of the PCV-weighted total-distribution values of all brands *b* (= 1, … B) in category *c*. The share of PCV-weighted total distribution reflects the aggregated SKU-distribution percentage points relative to the sum of all distribution percentage points in the category. Therefore, this metric represents a brand's share of the cumulated category distribution.

$$\%TDPCV_{bc} = \frac{TDPCV_{bc}}{\sum_{b=1}^{B} TDPCV_{bc}} \tag{12}$$

4.3 Modeling total-distribution velocity

We consider five model types for estimating the relationship between PCV-weighted total distribution and market share[7]. In all models, $\%MS_{bc}$ represents the average weekly market share of brand b in category c, and ε_{bct} is the error term capturing all external factors affecting market share not described by the share of PCV-weighted total distribution, $\%TDPCV_{bc}$. The models are estimated for each category.

Model 1: quadratic model. The first model type we consider is a quadratic (or second-order polynomial) model as used by Wilbur & Farris (2014). The authors develop a set of quadratic models to describe the relationship between ACV-weighted distribution and market share at the SKU and brand levels. In contrast, in this study, we test this model to estimate distribution velocity based on $\%TDPCV_{bc}$.

$$MS_{bc} = B_0 + (\%TDPCV_{bc})B_1 + (\%TDPCV_{bc})^2 B_2 + \varepsilon_{bc} \tag{13}$$

Model 2: rational-function model. We apply the rational-function model based on Reibstein and Farris's (1995) work. This model is one of the seminal models in describing the relationship between distribution and market share. It was initially built to describe brand-level distribution breadth and was later also tested for SKUs (Kruger & Harper, 2006). For both approaches, the model yielded comparably good fit values across various markets and product categories. An important advantage of rational-function models, such as the one developed by

[7] We expect the share of PCV-weighted total distribution and market share to be highly correlated. This should be reflected in relatively high values of the coefficient of determination (R-squared) across all categories for all tested model types.

Reibstein and Farris (1995), is that they can take a wide range of curve patterns, such as convex, concave, s-shaped, and inverse s-shaped.

$$MS_{bc} = \frac{B_0 * (\%TDPCV_{bc})^{B_1}}{(1-\%TDPCV_{bc})^{B_2}} + \varepsilon_{bc} \quad \text{where } B_0, B_1, B_2 \in \mathbb{R}+ \qquad (14)$$ [8]

Model 3: fractional-root model. Fractional-root (or multiplicative) models are frequently used for marketing-mix modeling (Danaher et al., 2008; Kumar et al., 2015). An advantage of this type of model is its simple but flexible form. Depending on the parameters, a fractional-root model can reflect increasing, decreasing, or constant returns to scale.

$$MS_{bc} = B_0 + B_1(\%TDPCV_{bc})^{B_2} + \varepsilon_{bc} \qquad (15)$$

Model 4: linear model. The simplest approach to model the relationship between $\%TDPCV_{bc}$ and $\%MS_{bc}$ is with a linear (or first-order polynomial) model. Prior literature has also suggested that distribution velocity based on total distribution may follow a linear curve pattern (Ailawadi & Farris, 2020). We consider this model because from visual inspection, the data appears to have a linear or nearly linear curve pattern.

$$MS_{bc} = B_0 + (\%TDPCV_{bc})B_1 + \varepsilon_{bc} \qquad (16)$$

Model 5: exponential model. The exponential model provides a functional form that is commonly used in marketing research to describe situations with increasing returns to scale (Hanssens et al., 2001). Visual inspection of the category scatterplots shows that such a relationship could be present in our data.

$$MS_{bc} = B_0 * e^{(\%TDPCV_{bc})B_1} + \varepsilon_{bc} \qquad (17)$$

5 Results

[8] Following prior literature (e.g., Hirche et al., 2021b), we restrict the rational-function model to positive parameter values. Without constraining the parameters, the model results in unrealistic curve patterns (e.g., a market share above 100%).

5.1 Model-free evidence for the relationship between distribution and market share

The resulting curve patterns from the distribution-velocity models vary depending on whether distribution breadth or total distribution are used. Figure 1 shows the curve patterns for two exemplary categories when using either the average weekly brand PCV, $\%PCV_{bc}$ (left), or the share of PCV-weighted total distribution, $\%TDPCV_{bc}$ (right). Whereas the curve pattern for $\%TDPCV_{bc}$ appears approximately linear, distribution measured with $\%PCV_{bc}$ follows a convex curve pattern. After a certain threshold of distribution, market share increases significantly. We observe this convex curve pattern in all product categories, replicating the findings from prior literature on the relationship between distribution breadth and market share (e.g., Kruger & Harper, 2006; Wilbur & Farris, 2014). Appendix A shows the distribution velocity of all categories for both metrics.

[insert Figure 1 here]

Figure 1 and Appendix A highlight that distribution breadth ($\%PCV_{bc}$) does not adequately explain the differences in market share between brands with high distribution coverage. For brands at the higher end of distribution coverage, there is strong variability in market share although their distribution levels are similar (i.e., lower variability). Moreover, increasing distribution breadth has only a marginal influence on market share for brands at the lower end of the market-share spectrum. Including distribution depth into a combined metric of total distribution ($\%TDPCV_{bc}$) reveals differences in distribution between brands that are not visible when using distribution breadth alone. These results further underscore the relevance of using a total-distribution metric when assessing a brand's distribution relative to the competition.

While Figure 1 compares curve patterns resulting from distribution-breadth versus total-distribution metrics, Figure 2 shows curve patterns based on total distribution for additional categories. Visual inspection reveals that brands with low market shares tend to “stretch” along the distribution scale, in stark contrast to previous findings in the literature based on distribution-breadth metrics showing that low-share brands typically cluster at the lower end of the scale (Farris et al., 1989; Kruger & Harper, 2006; Wilbur & Farris, 2014). For brands with higher levels of distribution and higher market shares, dispersion increases. This is an important finding that highlights the advantage of using a total-distribution metric when modeling distribution velocity as opposed to conventional distribution-breadth metrics.

Figure 2 also reveals that the evolution of the curve pattern when using a total-distribution metric may depend on the category in question. More specifically, the number of brands per category, their concentration along the scales, and their variability in terms of distribution velocity could result in different curve patterns. This circumstance may require a category-specific evaluation and modeling approach. A one-model-fits-all generalization may not be adequate in this regard.

5.2 Estimating distribution-velocity models

We estimate all distribution-velocity models using R programming language (R Core Team, 2021). For non-linear models, we use the nlstools package (Baty et al., 2015). Note that distribution-velocity models do not imply a causal effect of distribution on market share; rather, the focus is on describing the general curve pattern of the relationship and assessing the fit of the estimated models. Table 3 reports the model diagnostics. To assess how well the different models fit the data, we use root mean square error (RMSE) and R-squared.[9] While RMSE describes the average distance between the estimated and actual values in absolute terms, R-squared indicates how well the predictor variable explains variation in the response variable as a

[9] We use R-squared because all models have only one predictor variable.

percentage value. Both criteria are useful to assess the fit of a model (Chicco et al., 2021; Hanssens et al., 2001). We consider the standard deviation (σ) of R-squared for each distribution-velocity model to assess differences in model fit across categories. For RMSE, means and standard deviations are not applicable because absolute deviations differ in their interpretation across categories.

[insert Table 3 here]

Most of the distribution-velocity models provide very good fit values. For the quadratic model (mean R-squared = 0.895, i.e., total distribution accounts for 89.53% of the variation in market share on average), the rational-function model (mean R-squared = 0.895), and the fractional-root model (mean R-squared = 0.892) the average fit values are almost identical. Surprisingly, contrary to prior expectations from the literature (Ailawadi & Farris, 2020), the linear model performs worse than three of the other four other models (mean R-squared = 0.879, σ = 0.117). Overall, our results suggest that distribution velocity based on total distribution has a nonlinear (although nearly linear) relationship. The exponential model shows the worst fit (mean R-squared = 0.763, σ = 0.168). Furthermore, except for the exponential model, model fit seems robust across most categories. That is, the standard deviation of R-squared is very similar for the linear, quadratic, fractional-root, and rational-function models. The high standard deviation of R-squared for the exponential model appears to be primarily due to poor model fit in the bottled water category.

Bottled water is also the only category in which none of the five distribution-velocity models shows satisfactory fit (mean R-Squared = 0.505 and mean RMSE = 0.008 across all five models). This result might be due to the data structure in this category (see Figure 3).

Specifically, visual examination of the scatter plot shows that there are outliers in this category as brands with medium shares of total distribution have unusually high market shares.

Sensitivity to the variability of observations is central to distribution-velocity models based on total distribution because most market-share variation occurs for brands in the high market share–high distribution range, which contains only a small number of brands by nature. A total-distribution metric facilitates modeling because it "declutters" observations along the distribution scale. The five distribution-velocity models fit the data well in nine out of 10 categories. This indicates that the best performing models are probably generally applicable to a broad range of CPG categories.

Table 4 shows the resulting curve patterns for each model and category. A model has a convex curve pattern if its second derivative is positive. Vice versa, a model has a concave curve pattern if the second derivative is negative. If the second derivative is both positive and negative, the model has either an S-shaped or inverse S-shaped curve pattern based on the sequence of convexity and concavity. Note that the functional forms of both the linear and exponential models dictate their respective curve patterns—both are less flexible and therefore result in the same (linear and convex, respectively, curve patterns across categories). Appendix B provides the underlying parameter estimates. The quadratic model results in a convex curve pattern in six out of 10 categories and in a concave curve pattern in four categories. The rational-function model is convex in five out of 10 categories, concave in three categories, and inverse S-shaped in two categories. The fractional-root model yields a convex curve pattern in seven out of 10 categories and a concave curve pattern in three categories. When comparing the three flexible models—namely the quadratic, rational-function, and fractional-root models—we find that they largely (i.e., in seven out of 10 categories) present the same curve pattern. This finding highlights the need for model flexibility as categories may differ in curve pattern, so the distribution-velocity model used should be able to account for this.

Furthermore, Table 4 indicates that the relationship between the share of PCV-weighted total distribution and market share (i.e., distribution velocity) follows a convex curve pattern in most categories. Further evaluation through visual examination of the curve patterns shows that they appear to be linear for some categories, indicating that the degree of convexity or concavity is relatively small. However, the model diagnostics (Table 3) and identified curve patterns (Table 4) suggest that distribution velocity based on a total-distribution metric displays nonlinear, rather than strictly linear, patterns.

[insert Table 4 here]

Figure 3 shows the estimated distribution velocity for each model type and the observed values for the exemplary category "ground and whole bean coffee." All five model types estimate increasing market share with increasing total distribution. The deviation of observations above and below the distribution-velocity curve increases with higher levels of total distribution and market share. When visually examining the graphs in Figure 3, the estimated convex near-linear curve patterns for the flexible models (quadratic, fractional-root, rational-function models) are evident despite their relatively flat slopes. Furthermore, Figure 3 shows that the exponential model lacks the ability to adjust to near-linear curve patterns, as indicated by the distribution of observations in this category. This deficiency is likely due to the fact that the functional form forces the curve pattern to be explicitly convex, thereby underestimating market share to a substantial extent.

[insert Figure 3 here]

Appendix C shows the estimated distribution velocity and the observed values for all categories. Across all categories, the model-fit conditions described above exist. Flexible model types that allow for partial concave and convex curve intervals fit the data very well, and they are able to approach near-linearity, which is an important characteristic of distribution velocity based on a total-distribution metric. In addition to Appendix C, the examples in Appendix A show the differences in distribution velocity between a conventional distribution-breadth metric (i.e., strong convex curve pattern) and a total-distribution metric (i.e., near-linear curve pattern). The latter ensures that brands in the category with high distribution become less cluttered. This condition facilitates the estimation of distribution velocity (statistical modeling) and allows for better comparisons between brands (benchmarking).

6 Discussion

Based on retail scanner data from the U.S. market covering a total of 1,682 brands in 12,049 stores across five channel types, this article demonstrates the usefulness of a total-distribution metric, which combines the two dimensions of distribution breadth and depth. We show that such a metric is particularly helpful when measuring the distribution velocity of brands. We also systematically compare five distribution-velocity models based on total distribution to inform theory and practice about their application potential. We highlight that a total-distribution metric, in comparison to conventional distribution-breadth metrics, allows for a less cluttered and more realistic representation of distribution velocity. Because of this better representation, total distribution facilitates the modeling of distribution velocity and, consequently, the ability to meaningfully compare brands with their expected values (estimates) and with each other in a given category and market. We identify those model types that best fit the data, thereby providing guidance to researchers and managers in selecting appropriate distribution-velocity models. Therefore, our main contribution lies in the development of distribution-velocity models based on total distribution. These models provide a more nuanced understanding of distribution velocity by incorporating both distribution breadth and depth and can be used as a robust analytical tool to dissect market-share dynamics. Specifically, this approach of combining distribution breadth and depth provides insights for competitive analysis to support strategic decision-making. In the following, we discuss this work's contributions and implications for theory and practice in more detail.

6.1 Theoretical implications

Prior literature has primarily focused on distribution breadth when investigating the distribution velocity of brands (e.g., Ailawadi & Farris 2020; Hirche et al. 2021a; Kruger & Harper 2006). However, distribution breadth only accounts for the number of stores in which a product is sold, typically weighted by the stores' total or category sales. The additional measurement of distribution depth, meaning how many of a brand's SKUs are sold in a store, is critical for a holistic competitive analysis of distribution. Against this background, we discuss and empirically validate total distribution as a suitable metric to measure distribution velocity.

Furthermore, although prior literature has proposed statistical models to estimate distribution velocity, these models do not account for both dimensions of distribution (e.g., Farris et al., 1989; Hirche et al. 2021b; Reibstein & Farris 1995; Wilbur & Farris, 2014). We address this gap by systematically analyzing the relationship between total distribution and market share (i.e., distribution velocity) and by estimating and comparing different distribution-velocity models that consider both distribution breadth and depth. We show that using a total-distribution metric enables a more granular picture of a brand's distribution coverage, especially at high distribution levels, which offers substantive benefits for analyzing and interpreting distribution velocity.

The results show that models used to estimate distribution velocity based on total distribution require sufficient flexibility in their curve pattern. In contrast to suggestions in prior literature (Ailawadi & Farris, 2020), our findings show that distribution velocity based on total distribution does not follow a strictly linear curve pattern. Flexible model types that allow for partial concave and convex curve intervals (e.g., quadratic, fractional-root, rational-function models) fit the data very well because they are able to approach near-linearity as well as distinct convexity or concavity. However, depending on the category, even a simple linear model could provide good fit—an option that is generally unfeasible with conventional distribution-breadth metrics.

In addition, we provide further support for the existence of the "double jeopardy" phenomenon identified in prior research, which refers to how brands with high market shares tend to sell more per additional point of distribution (Farris et al., 1989; Kruger & Harper, 2006; Wilbur & Farris, 2014). This phenomenon is more obvious in the curve patterns based on distribution-breadth metrics; however, the distribution-velocity curves presented in this article demonstrate that distribution depth (i.e., the number of a brand's SKUs) is associated with the phenomenon. Hence, our finding indicates that brands with high market shares sell more not only per additional stocking outlet but also per additional SKU introduced in those stocking outlets.

The results also suggest that model fit and, consequently, the choice of a suitable model may depend on the individual category data. Therefore, we do not recommend a generalized modeling approach but rather a selective one across categories. For example, categories differ in their number of brands (i.e., number of datapoints), and the number of datapoints should be taken into account when modeling distribution velocity. Specifically, since total-distribution velocity curves are necessarily based on brand-level data, they logically contain fewer datapoints compared to those based on SKU-level data, particularly at the high ends of the distribution and market-share scales. Furthermore, categories may contain niche brands with above-expected market shares relative to distribution, which may also affect model fit.

However, deviations from expected distribution velocity also offer opportunities to further investigate the nature of these brands. For example, it could be interesting to apply analytical approaches, such as machine learning, to predict over- and underperforming brands and to identify their unique characteristics (Hirche et al., 2021b). Likewise, total distribution could be used in semiparametric sales modeling including additional marketing-mix variables to evaluate the impact of changes in retail distribution on sales (Michis, 2023).

6.2 Managerial implications

Our research offers a number of managerial implications. First, in contrast to the conventional assessment of distribution breadth only, this work provides managers with a more holistic view on a brand's distribution coverage by using total distribution, which combines distribution breadth and depth.

Second, by using a total-distribution metric, managers can evaluate a market's competitive distribution structure more accurately and determine whether a brand's current distribution level is likely to sustain over time (Ailawadi & Farris, 2020). Specifically, the proposed distribution-velocity models based on total distribution increase the variability of the distribution measure, especially for brands with higher distribution levels, thus allowing for more suitable model estimation compared to previous modeling approaches. Using these models, managers can track the impact of product-portfolio changes on distribution velocity and assess whether their brands' shares of total distribution are in line with their market-share goals and whether expectations regarding the impact of distribution efforts on distribution velocity are realistic. Therefore, distribution-velocity models based on total distribution offer a basis for more meaningful benchmarking and competitive analysis than conventional distribution metrics (i.e., breadth). Applying a competitive approach to evaluating distribution decisions is becoming increasingly important as the challenge of obtaining scarce shelf space increases (Venkatesan et al., 2015). Quantifying the impact of additional distribution on market share, and vice versa, can help managers assess how much of their budgets they should allocate to expanding their current distribution networks and to pull-oriented marketing efforts. The proposed velocity models based on total distribution can support these analyses by providing more precise modeling of the relationship between distribution and market share and more meaningful interpretation.

Third, analyzing distribution velocity helps evaluate a brand's fair share of distribution (see section 2.4), which is reflected in the velocity-model estimates. Practically, a brand's total distribution can be increased by adding SKUs (depth), distributing to more stores (breadth), or a combination of both to approximate its fair share of distribution. Prior literature has suggested that the relationship between a brand's market share and its share of total distribution relative to other brands in the particular category (i.e., its "fair share") is linear (Ailawadi & Farris, 2020; Nielsen IQ, 2020; Simon, 2013). Our findings largely confirm this linear relationship. However, we show that a strictly linear approach may not always describe this relationship. Some other velocity models based on total distribution could perform slightly better than the linear model. As such, whether or not a brand's current distribution velocity is in line with expectations is important to know, for example, when negotiating additional shelf space. Our findings show that even when other velocity models perform better than the linear model, the curves are still largely linear. A typical brand therefore could expect a similar market share to its share of distribution.

6.3 Limitations and research directions

This research offers interesting avenues for future research. First, we evaluated the relationship between PCV-weighted total distribution and market share at the brand level across various categories, excluding store-level variations. This approach was chosen for simplicity and generalizability but may overlook local market and store-specific conditions, and intra-brand competition which could influence distribution effectiveness. Incorporating store-level data into the analysis could enrich the understanding of how local conditions and competitive dynamics at the store level affect distribution strategies. Hierarchical or mixed-effects models could be particularly useful in this context, allowing researchers to assess the impact of regional market conditions and store characteristics on distribution success. Future research could extend this analysis by assessing this relationship at a more granular level, focusing on, for example, subsections of the total-distribution scale or even clusters of brands. For example, managers might gain even more useful insights when comparing a brand's position to close competitors in specific distribution channels rather than the whole market.

Second, in our study, we aggregated weekly data into annual metrics to simplify the analysis and focus on long-term trends. While this approach aids in reducing noise and highlighting broader trends, it potentially overlooks seasonal variations and short-term dynamics that might be critical for understanding distribution impacts more deeply. Future studies could incorporate a more granular temporal analysis that captures seasonal trends and short-term effects.

Third, there are certainly opportunities to investigate the causal effects of distribution velocity, for example, by conducting quasi-experiments (Goldfarb et al., 2022). Effects related to portfolio changes (manufacturer) as well as assortment changes (retailer) may be of particular interest given the challenges manufacturers face with respect to listing and delisting decisions.

Fourth, our current study primarily utilizes data from conventional retail channels, potentially limiting its applicability to the rapidly growing e-commerce sector, where distribution dynamics can be substantially different. Future research should consider extending the analysis to include e-commerce platforms and digital distribution channels. This expansion would not only broaden the applicability of the findings but also allow for a comparative analysis between traditional and digital retail environments. Advanced analytics techniques that parse digital consumer behavior and online sales patterns could provide new insights into distribution strategies tailored for the digital age.

Fifth, future research could examine potential reasons why brands may deviate from their fair shares (i.e., why they deviate from their velocity-model estimates). Identifying the factors that allow brands to persist above or below their expected distribution velocities could help managers assess whether the positions of their brands are legitimate or if there is room for improvement.

Finally, the distribution velocity derived from our data is a snapshot of the market structure for a one-year time period. Future research could examine how brands move along the distribution-velocity curve over time and dive deeper into evaluating whether brands that deviate from the expected distribution velocity can sustain their position over time or whether these brands will eventually move toward the expected values in their categories.

Table 1. Summary statistics of the stores included in the data

Channel Type	Number of Stores by State				Total	%
	California	New York	Texas	Wisconsin		
Drug	1,145	1,029	679	222	3,075	25.52
Food	1,789	558	752	257	3,356	27.85
Convenience	966	157	1,615	47	2,785	23.11
Mass Merchandise	640	484	1,437	203	2,764	22.94
Liquor	0	3	66	0	69	0.57
Total	4,540	2,231	4,549	729	12,049	100.00

Table 2. Summary statistics of the brands and categories included in the data

Category	Revenue ($M)	SKUs	Brands	Brand Market Share (%) Mean	Brand Market Share (%) Median	Brand Market Share (%) Max.	Brand Distribution (%) PCV Mean	Brand Distribution (%) PCV Median	Brand Distribution (%) PCV Max.	Brand Distribution (%) Total Distribution Mean	Brand Distribution (%) Total Distribution Median	Brand Distribution (%) Total Distribution Max.
Dairy Milk Refrigerated	1,236	775	123	0.81	0.03	20.84	7.44	0.83	94.57	0.81	0.06	21.49
Dental Floss	90	142	62	1.61	0.20	19.72	21.77	3.18	94.50	1.61	0.23	18.29
Deodorants - Personal	703	1,242	201	0.50	0.01	14.70	20.99	1.99	97.71	0.50	0.01	14.30
Detergents - Packaged	113	229	56	1.79	0.04	25.49	11.92	0.93	90.28	1.79	0.07	20.09
Facial Tissues	114	240	43	2.33	0.01	52.34	8.07	0.17	98.43	2.33	0.01	40.44
Ground & Whole Bean Coffee	1,538	2,891	401	0.25	0.01	10.64	10.50	0.77	95.35	0.25	0.01	7.58
Pasta - Spaghetti	139	636	162	0.62	0.01	48.32	6.82	1.37	91.08	0.62	0.07	25.09
Potato Chips	1,248	1,191	132	0.76	0.01	38.07	13.02	1.31	97.14	0.76	0.03	25.20
Soap - Liquid	166	706	120	0.83	0.01	22.71	10.19	0.28	91.02	0.83	0.01	17.32
Water - Bottled	1,966	1,572	382	0.26	0.01	10.81	8.88	0.89	98.95	0.26	0.01	5.93
Mean	731	962	168	0.98	0.03	26.36	11.96	1.96	94.90	0.98	0.05	19.57
Total	7,313	9,624	1,682	-	-	-	-	-	-	-	-	-

Note: According to Ailawadi & Farris (2020) the ratio between market share and share of total distribution is proportional, and as a graph averages to a diagonal (45°). This is the reason why both metrics inherently have identical values. All percentages are scaled between 0 and 100.

Table 3. Model diagnostics

Category	Quadratic Model		Rational-Function Model		Fractional-Root Model		Linear Model		Exponential Model	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Dairy Milk Refrigerated	0.929	0.008	0.929	0.008	0.930	0.008	0.929	0.008	0.781	0.014
Dental Floss	0.911	0.009	0.911	0.009	0.911	0.009	0.910	0.010	0.718	0.017
Deodorants - Personal	0.986	0.002	0.985	0.002	0.985	0.002	0.985	0.002	0.827	0.008
Detergents - Packaged	0.967	0.009	0.967	0.009	0.967	0.009	0.960	0.010	0.913	0.015
Facial Tissues	0.903	0.028	0.900	0.028	0.900	0.028	0.900	0.028	0.817	0.038
Ground & Whole Bean Coffee	0.893	0.003	0.894	0.003	0.894	0.003	0.885	0.004	0.710	0.006
Pasta - Spaghetti	0.961	0.008	0.979	0.006	0.959	0.008	0.883	0.013	0.953	0.009
Potato Chips	0.932	0.010	0.939	0.009	0.927	0.010	0.899	0.012	0.860	0.014
Soap - Liquid	0.898	0.010	0.898	0.010	0.898	0.010	0.897	0.010	0.734	0.016
Water - Bottled	0.573	0.008	0.545	0.008	0.547	0.008	0.542	0.008	0.316	0.010
Mean	0.895	-	0.895	-	0.892	-	0.879	-	0.763	-
σ	0.112	-	0.121	-	0.119	-	0.117	-	0.168	-

Note: As a robustness check, we replicated the analysis with historical data from 2009, but replaced dollar market share with unit market share. This allows us to check whether the relatively high R-squared values are due to the fact that both metrics (i.e., share of PCV-weighted total distribution and market share) have operational similarities as they both reflect shares of a total market, the former in terms of distribution and the latter in terms of sales. The results are robust regarding model diagnostics (i.e., minimal differences in R-squared values) and the curve patterns of the velocity graphs reported in Table 4 (i.e., only 10% of curve patterns changed), supporting this assumption.

Table 4. Model curve patterns

Category	Quadratic Model	Rational-Function Model	Fractional-Root Model	Linear Model	Exponential Model
Dairy Milk Refrigerated	Concave (near linear)	Convex (near linear)	Convex (near linear)	Linear	Convex
Dental Floss	Convex (near linear)	Convex (near linear)	Convex (near linear)	Linear	Convex
Deodorants - Personal	Concave (near linear)	Concave (near linear)	Concave (near linear)	Linear	Convex
Detergents - Packaged	Convex	Convex	Convex	Linear	Convex
Facial Tissues	Concave	Concave (near linear)	Concave (near linear)	Linear	Convex
Ground & Whole Bean Coffee	Convex (near linear)	Convex (near linear)	Convex (near linear)	Linear	Convex
Pasta - Spaghetti	Convex	Inverse S-shaped	Convex	Linear	Convex
Potato Chips	Convex	Inverse S-shaped	Convex	Linear	Convex
Soap - Liquid	Convex (near linear)	Convex (near linear)	Convex (near linear)	Linear	Convex
Water - Bottled	Concave	Concave (near linear)	Concave (near linear)	Linear	Convex

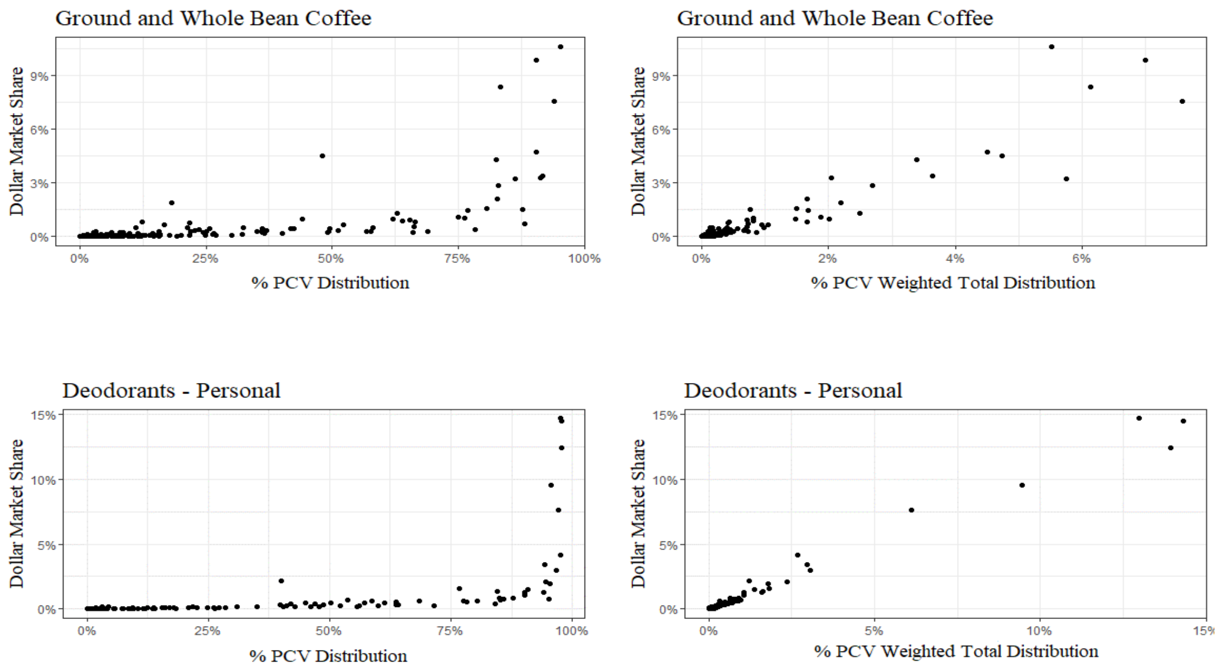


Figure 1. Distribution velocity in two categories when using a distribution-breadth (left) versus total-distribution (right) metric.

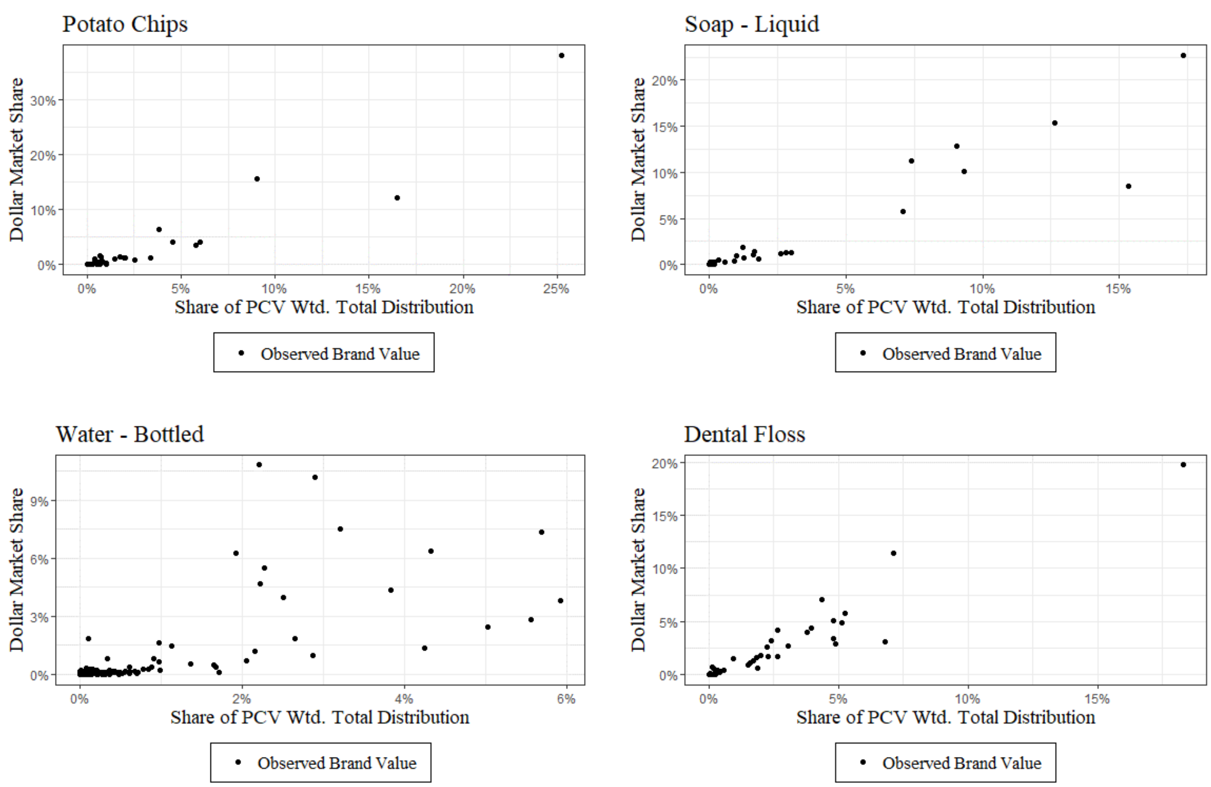


Figure 2. Total-distribution velocity for different categories.

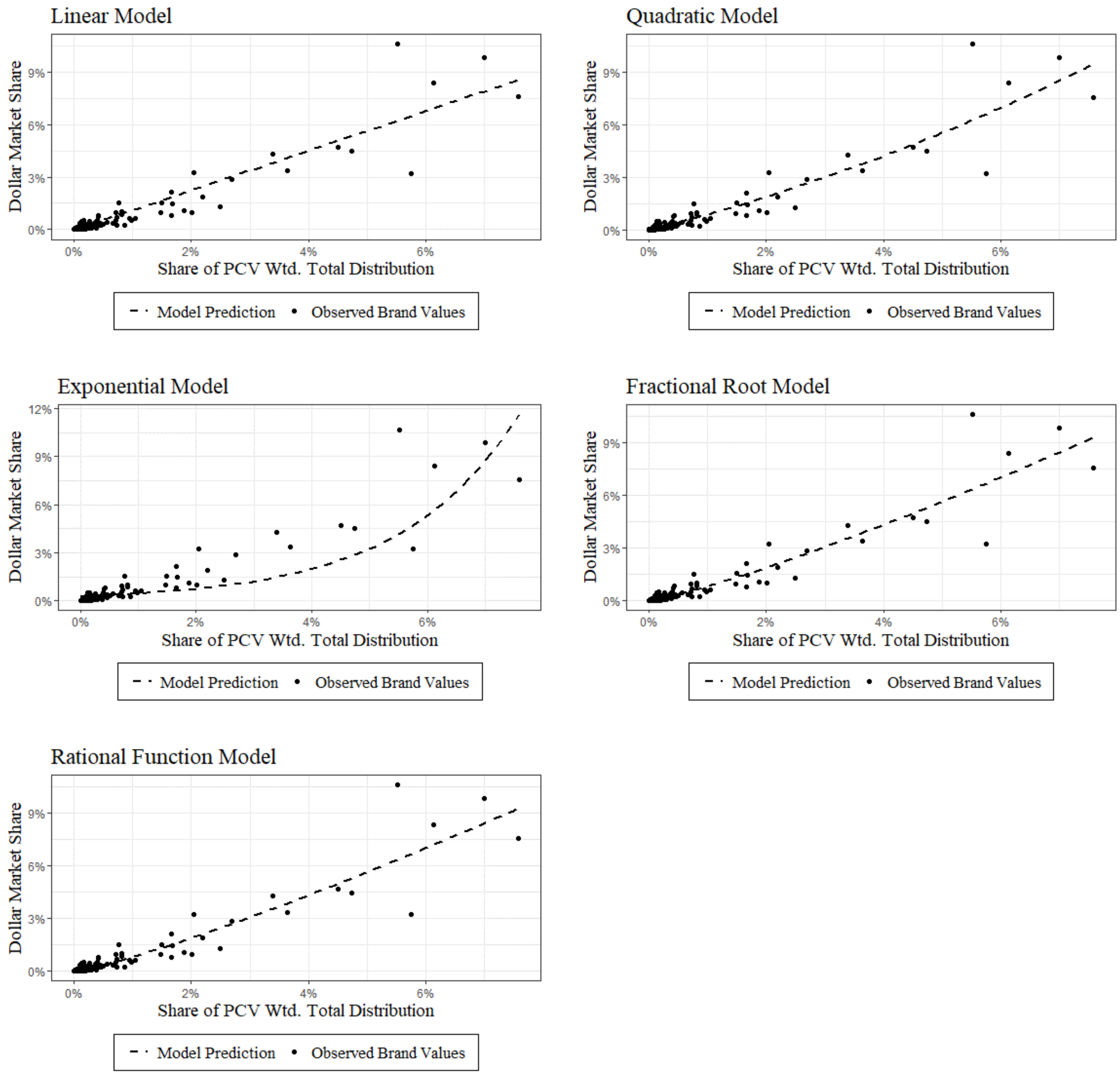


Figure 3. Distribution-velocity models for ground and whole bean coffee.

Declarations

Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Ailawadi, K. L., & Farris, P. W. (2017). Managing Multi-and Omni-Channel Distribution: Metrics and Research Directions. *Journal of Retailing*, *93*(1): 120-135. http://dx.doi.org/10.1016/j.jretai.2016.12.003

Ailawadi, K. L., & Farris, P. W. (2020). *Getting Multi-Channel Distribution Right*. John Wiley & Sons.

Ataman, M. B., Mela, C. F., & van Heerde, H. J. (2008). Building Brands. *Marketing Science*, *27*(6): 1036-1054. https://doi.org/10.1287/mksc.1080.0358

Ataman, M. B., Van Heerde, H. J., & Mela, C. F. (2010). The long-term effect of marketing strategy on brand sales. *Journal of Marketing Research*, *47*(5), 866-882. https://doi.org/10.1509/jmkr.47.5.866

Aurier, P., & Mejía, V. D. (2020). The interplay of brand-line assortment size and alignability in the sales of brand-lines and line-extensions of frequently purchased products. *Journal of Business Research*, 117: 163-175. https://doi.org/10.1016/j.jbusres.2020.05.024

Basuroy, S., Mantrala, M. K., & Walters, R. G. (2001). The impact of category management on retailer prices and performance: Theory and evidence. *Journal of Marketing*, *65*(4): 16-32. https://doi.org/10.1509/jmkg.65.4.16.18382

Baty, F., Ritz, C., Charles, S., Brutsche, M., Flandrois, J.-P., & Delignette-Muller, M.-L. (2015). A toolbox for nonlinear regression in R: the package nlstools. *Journal of Statistical Software*, *66*: 1-21. https://doi.org/10.18637/jss.v066.i05

Borin, N. A., Vranken, C. V., & Farris, P. W. (1991). A Pilot Test of Discrimination in the Japanese Distribution System. *Journal of Retailing*, *67*(1): 93-106.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of Marketing*, *73*(6): 1-17. https://doi.org/10.1509/jmkg.73.6.1

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, *7*: e623. https://doi.org/10.7717/peerj-cs.623

Danaher, P. J., Bonfrer, A., & Dhar, S. (2008). The effect of competitive advertising interference on sales of packaged goods. *Journal of Marketing Research*, *45*(2): 211-225. https://doi.org/10.1509/jmkr.45.2.211

Datta, H., Ailawadi, K. L. and van Heerde, H. J.,. (2017). How Well Does Consumer-Based Brand Equity Align with Sales-Based Brand Equity and Marketing-Mix Response? *Journal of Marketing Research*, *81*(3): 1-20. https://doi.org/10.1509/jm.15.0340

Desmet, P., & Renaudin, V. (1998). Estimation of product category sales responsiveness to allocated shelf space. *International Journal of Research in Marketing*, *15*(5): 443-457. https://doi.org/10.1016/S0167-8116(98)00018-4

Drèze, X., Hoch, S. J., & Purk, M. E. (1994). Shelf management and space elasticity. *Journal of Retailing*, *70*(4): 301-326. http://dx.doi.org/10.1016/0022-4359(94)90002-7

Eisend, M. (2014). Shelf space elasticity: A meta-analysis. *Journal of Retailing*, *90*(2): 168-181. https://doi.org/10.1016/j.jretai.2013.03.003

Farris, P. W. (2004). Using Steiner's dual-stage model to develop better measures of retail distribution. *The Antitrust Bulletin*, *49*(4): 941-954. https://doi.org/10.1177/0003603X0404900406

Farris, P. W., Bendle, N., Pfeifer, P. E., & Reibstein, D. J. (2016). *Marketing metrics: The manager's guide to measuring marketing performance* (3 ed.). Pearson.

Farris, P. W., Olver, J., & de Kluyver, C. (1989). The relationship between distribution and market share. *Marketing Science*, *8*(2): 107-128. https://doi.org/10.1287/mksc.8.2.107

Friberg, R., & Sanctuary, M. (2017). The Effect of Retail Distribution on Sales of Alcoholic Beverages. *Marketing Science*, *36*(4): 626-641. https://doi.org/10.1287/mksc.2017.1038

Guissoni, L. A., Rodrigues, J. M., Zambaldi, F., & Neves, M. F. (2020). Numeric or weighted distribution? The effect of different channel performance metrics on market share. *Journal of Marketing Channels*, *26*(2): 108-119. https://doi.org/10.1080/1046669X.2020.1742052

Hanssens, D., Parsons, L., & Schultz, R. (2001). *Market response models: Econometric and time series analysis*. Kluwer Academic Publishers.

Hirche, M., Farris, P. W., Greenacre, L., Quan, Y., & Wei, S. (2021b). Predicting Under-and Overperforming SKUs within the Distribution–Market Share Relationship. *Journal of Retailing*, *97*(4): 697-714. https://doi.org/10.1016/j.jretai.2021.04.002

Hirche, M., Greenacre, L., Nenycz-Thiel, M., Loose, S., & Lockshin, L. (2021a). SKU performance and distribution: A large-scale analysis of the role of product characteristics with store scanner data. *Journal of Retailing and Consumer Services*, *61*: 102533. https://doi.org/10.1016/j.jretconser.2021.102533

Jung, S.-U., Zhu, J., & Gruca, T. S. (2016). A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets. *Journal of Business Research*, 69(12): 5901-5908. https://doi.org/10.1016/j.jbusres.2016.04.106

Kruger, M. W., & Harper, B. (2006, June 09). *Market share and product distribution: Re-tested and extended* INFORMS Marketing Science Conference, Pittsburgh.

Kucuk, S. U. (2008). Can distribution explain double jeopardy patterns? *International Journal of Retail & Distribution Management*, *36*(5): 409-425. https://doi.org/10.1108/09590550810870120

Kumar, V., Sunder, S., & Sharma, A. (2015). Leveraging distribution to maximize firm performance in emerging markets. *Journal of Retailing*, *91*(4): 627-643. https://doi.org/10.1016/j.jretai.2014.08.005

Martinez-de-Albeniz, & Roels, G. (2011). Competing for shelf space. *Production and Operations Management*, *20*(1): 32-46. https://doi.org/10.1111/j.1937-5956.2010.01126.x

Michis, Antonis A. (2023). Retail distribution evaluation in brand-level sales response models. *Journal of Marketing Analytics*, *11*(3): 366-378. https://doi.org/10.1057/s41270-022-00165-8

Murray, C. C., Talukdar, D., & Gosavi, A. (2010). Joint optimization of product price, display orientation and shelf-space allocation in retail category management. *Journal of Retailing*, *86*(2): 125-136. https://doi.org/10.1016/j.jretai.2010.02.008

Neslin, S. A. (1990). A market response model for coupon promotions. *Marketing Science*, *9*(2): 125-145. https://doi.org/10.1287/mksc.9.2.125

Nielsen IQ. (2020). *Understanding Total Distribution Points*. https://nielseniq.com/wp-content/uploads/sites/4/2021/02/ConnectedSystem-Job-Aid-Understanding-TDPs.pdf

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.r-project.org

Reibstein, D. J., & Farris, P. W. (1995). Market share and distribution: A generalization, a speculation, and some implications. *Marketing Science*, *14*(3, part 2): G190-G202. https://doi.org/10.1287/mksc.14.3.G190

Simon, R. (2013). *Are You Getting Your Fair Share of Distribution?* https://www.cpgdatainsights.com/distribution/fair-share-of-distribution/

Slotegraaf, R. J., Moorman, C., & Inman, J. J. (2003). The role of firm resources in returns to market deployment. *Journal of Marketing Research*, *40*(3): 295-309. https://doi.org/10.1509/jmkr.40.3.295.19235

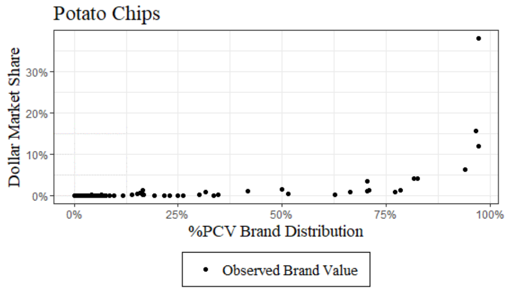
Srinivasan, S., Vanhuele, M., & Pauwels, K. (2010). Mind-Set Metrics in Market Response Models: An Integrative Approach. *Journal of Marketing Research*, *47*(4): 672-684. https://doi.org/10.1509/jmkr.47.4.672

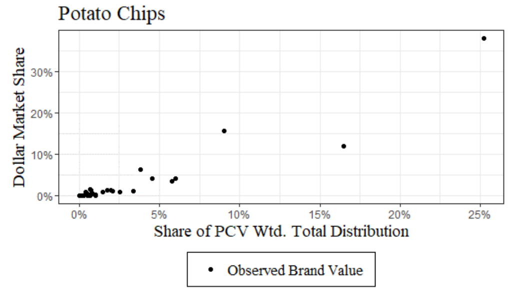
Venkatesan, R., Farris, P. W., Guissoni, L. A., & Neves, M. F. (2015). Consumer brand marketing through full-and self-service channels in an emerging economy. *Journal of Retailing*, *91*(4): 644-659. https://doi.org/10.1016/j.jretai.2015.04.003

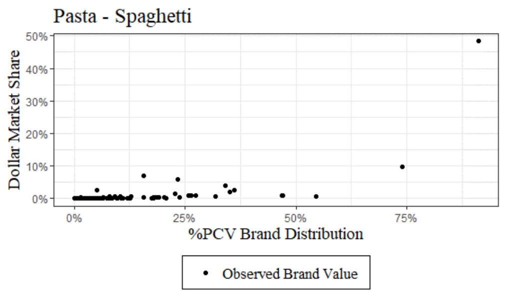
Wilbur, K., & Farris, P. W. (2014). Distribution and market share. *Journal of Retailing*, *90*(2): 154-167. https://doi.org/10.1016/j.jretai.2013.08.003

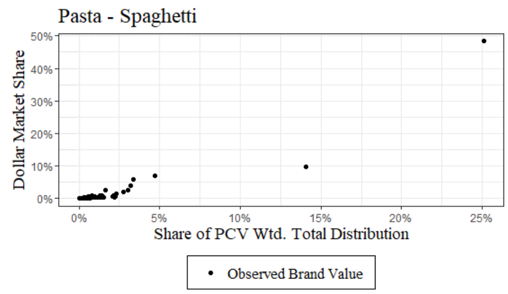
Appendixes

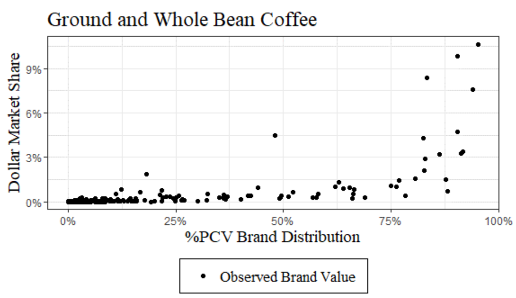
Appendix A: Metric comparisons per category

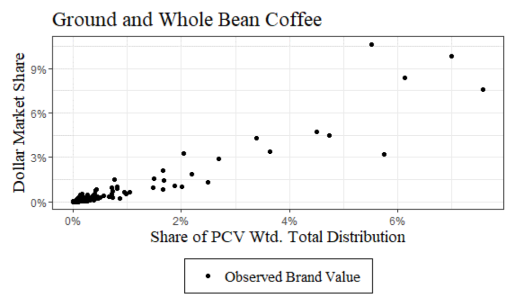


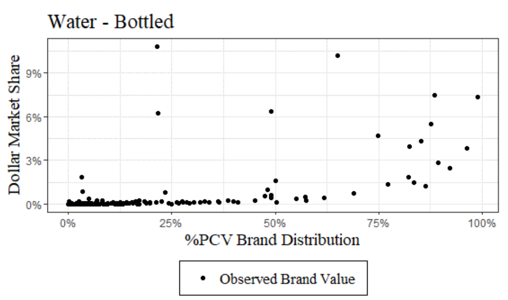


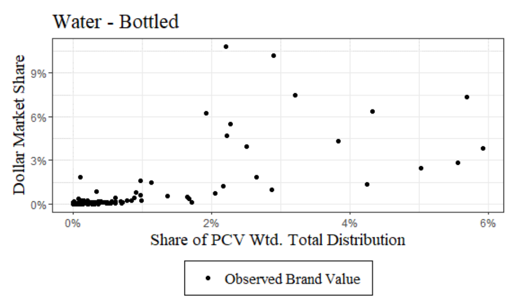


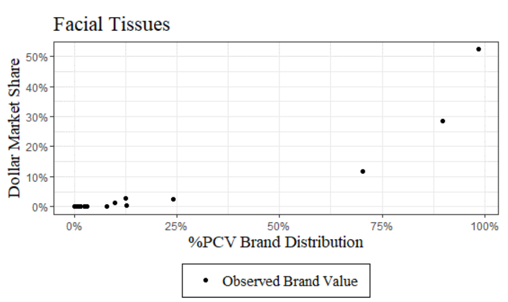


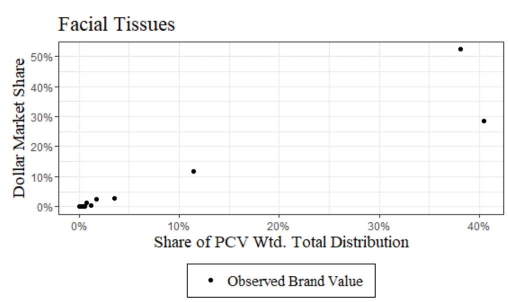


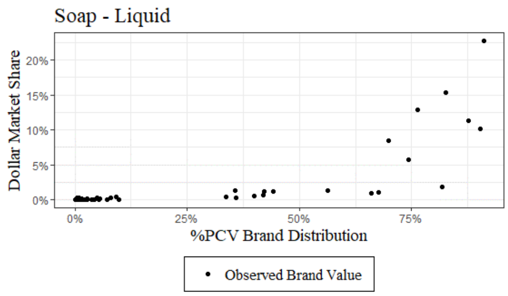


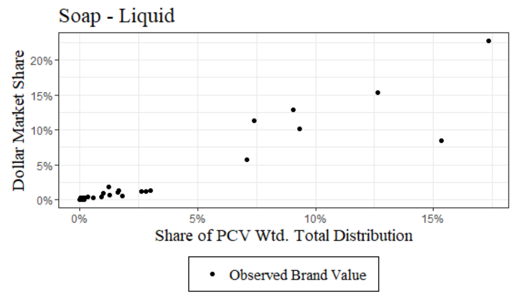


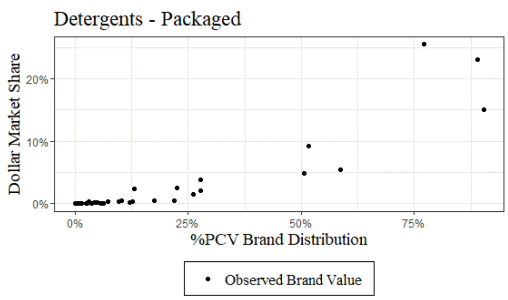


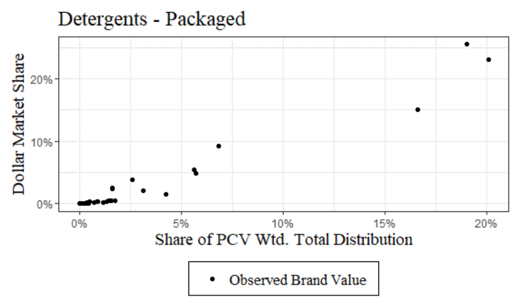


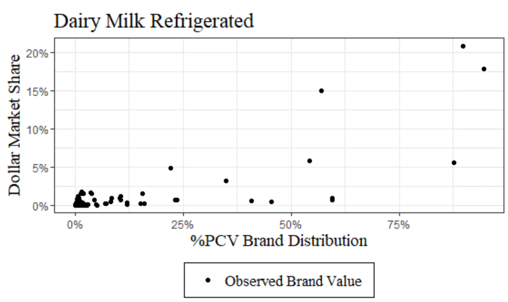


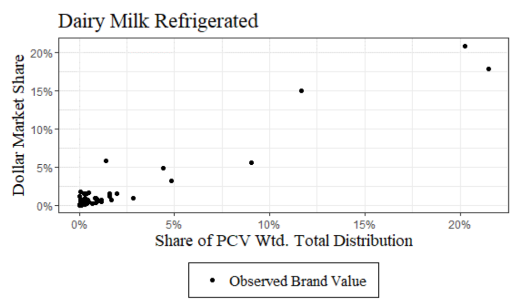

Soap - Liquid
Dollar Market Share
0%
5%
10%
15%
20%
0%
25%
50%
75%
%PCV Brand Distribution
Observed Brand Value

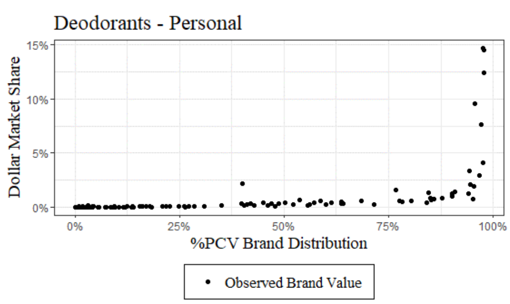

Soap - Liquid
Dollar Market Share
0%
5%
10%
15%
20%
0%
5%
10%
15%
Share of PCV Wtd. Total Distribution
Observed Brand Value

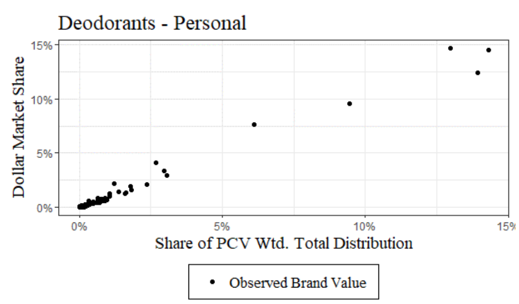

Detergents - Packaged
Dollar Market Share
0%
10%
20%
0%
25%
50%
75%
%PCV Brand Distribution
Observed Brand Value

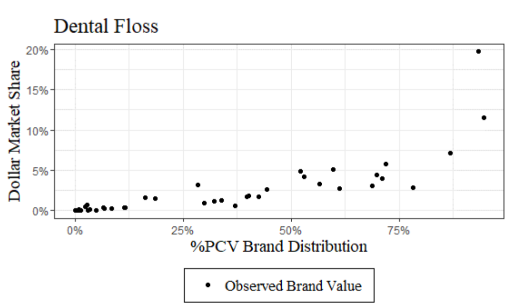

Detergents - Packaged
Dollar Market Share
0%
10%
20%
0%
5%
10%
15%
20%
Share of PCV Wtd. Total Distribution
Observed Brand Value

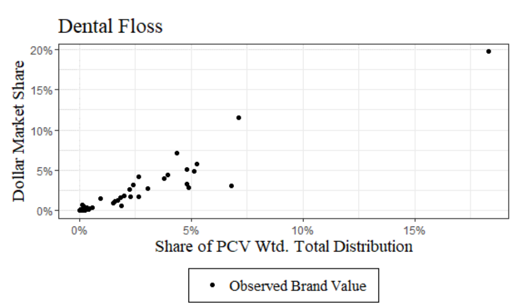

Dairy Milk Refrigerated
Dollar Market Share
0%
5%
10%
15%
20%
0%
25%
50%
75%
%PCV Brand Distribution
Observed Brand Value


Dairy Milk Refrigerated
Dollar Market Share
0%
5%
10%
15%
20%
0%
5%
10%
15%
20%
Share of PCV Wtd. Total Distribution
Observed Brand Value


Deodorants - Personal
Dollar Market Share
0%
5%
10%
15%
0%
25%
50%
75%
100%
%PCV Brand Distribution
Observed Brand Value


Deodorants - Personal
Dollar Market Share
0%
5%
10%
15%
0%
5%
10%
Share of PCV Wtd. Total Distribution
Observed Brand Value


Dental Floss
Dollar Market Share
0%
5%
10%
15%
20%
0%
25%
50%
75%
%PCV Brand Distribution
Observed Brand Value


Dental Floss
Dollar Market Share
0%
5%
10%
15%
20%
0%
5%
10%
15%
Share of PCV Wtd. Total Distribution
Observed Brand Value

Appendix B: Parameter estimates

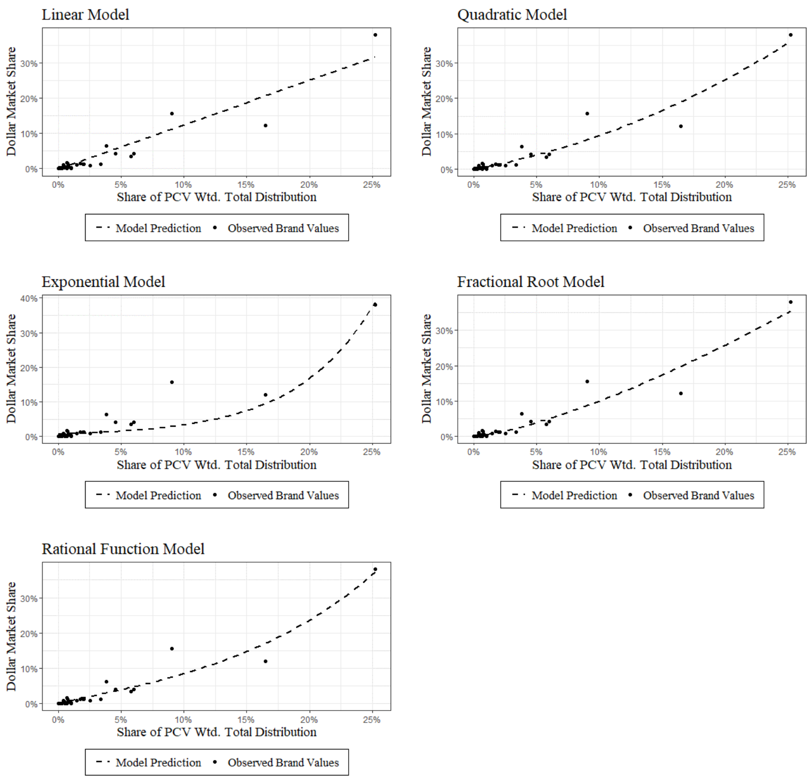
Category	B_0	t-Value	B_1	t-Value	B_2	t-Value
Linear Model (n)						
Potato Chips (132)	-0.0020	-1.8153	1.2592***	34.1011	-	-
Pasta - Spaghetti (162)	-0.0036**	-3.2828	1.5842***	34.7216	-	-
Ground and Whole Bean Coffee (401)	-0.0003	-1.7861	1.1331***	55.4388	-	-
Water - Bottled (382)	-0.0002	-0.4762	1.0775***	21.1941	-	-
Dairy Milk Refrigerated (123)	0.0005	0.7581	0.9329***	39.9166	-	-
Detergents - Packaged (56)	-0.0026	-1.7640	1.1455***	36.0894	-	-
Soap - Liquid (120)	-0.0006	-0.6079	1.0704***	32.1176	-	-
Facial Tissues (43)	-0.0004	-0.0973	1.0193***	19.1844	-	-
Deodorants - Personal (201)	-0.0001	-0.6873	1.0243***	112.6908	-	-
Dental Floss (62)	-0.0009	-0.6238	1.0543***	24.5862	-	-
Quadratic Model (n)						
Potato Chips (132)	0.0001	0.0984	0.6273***	7.3198	3.1832***	7.8896
Pasta - Spaghetti (162)	0.0008	1.2394	0.2720***	3.4841	6.2923***	17.8611
Ground and Whole Bean Coffee (401)	0.0000	-0.2308	0.8368***	14.5685	5.4471***	5.4926
Water - Bottled (382)	-0.0009*	-2.0121	1.7592***	12.7193	-15.9380***	-5.2726
Dairy Milk Refrigerated (123)	0.0005	0.6702	0.9456***	11.6206	-0.0695	-0.1633
Detergents - Packaged (56)	-0.0006	-0.3969	0.7949***	7.1959	1.9739**	3.2917
Soap - Liquid (120)	-0.0005	-0.5061	1.0298***	9.2318	0.3030	0.3814
Facial Tissues (43)	-0.0018	-0.3787	1.3862***	4.1951	-0.9545	-1.1250
Deodorants - Personal (201)	-0.0004*	-2.1342	1.1588***	36.5387	-1.0945***	-4.4095
Dental Floss (62)	-0.0003	-0.1715	0.9781***	10.7393	0.5755	0.9488
Exponential Model (n)						
Potato Chips (132)	0.0066***	6.1851	16.2032***	24.2921	-	-
Pasta - Spaghetti (162)	0.0044***	7.6306	18.7579***	35.4457	-	-
Ground and Whole Bean Coffee (401)	0.0027***	11.0036	49.4953***	35.4236	-	-
Water - Bottled (382)	0.0029***	6.3777	52.6843***	16.0648	-	-
Dairy Milk Refrigerated (123)	0.0069***	6.0976	16.0421***	19.5200	-	-
Detergents - Packaged (56)	0.0086***	5.0035	17.0304***	16.0208	-	-
Soap - Liquid (120)	0.0072***	5.6053	19.8757***	17.1636	-	-
Facial Tissues (43)	0.0126*	2.1872	8.6885***	7.4147	-	-
Deodorants - Personal (201)	0.0042***	8.1148	25.4195***	27.4277	-	-
Dental Floss (62)	0.0122***	6.5356	15.5034***	15.8127	-	-
Fractional-Root Model (n)						
Potato Chips (132)	0.0006	0.6530	2.3712***	9.9401	1.3795***	22.0624
Pasta - Spaghetti (162)	0.0022***	3.4549	11.5603***	6.4325	2.3079***	21.1830
Ground and Whole Bean Coffee (401)	0.0001	0.5827	2.0625***	8.8930	1.2013***	31.4745
Water - Bottled (382)	-0.0006	-1.2579	0.6955***	4.1575	0.8640***	12.0530
Dairy Milk Refrigerated (123)	0.0007	0.8636	0.9669***	10.9398	1.0205***	20.2598

Category	B_0	t-Value	B_1	t-Value	B_2	t-Value
Detergents - Packaged (56)	-0.0001	-0.0856	1.6066***	8.2711	1.1934***	17.3195
Soap - Liquid (120)	-0.0003	-0.2547	1.2378***	6.5129	1.0706***	14.5382
Facial Tissues (43)	-0.0012	-0.2377	0.9597***	6.4072	0.9376***	6.2051
Deodorants - Personal (201)	-0.0003	-1.6512	0.9496***	29.1146	0.9649***	63.0695
Dental Floss (62)	0.0000	-0.0072	1.1957***	7.8426	1.0583***	18.5566
Rational-Function Model (n)						
Potato Chips (132)	0.3425	2.7640	0.7884***	7.1959	4.0240***	5.2168
Pasta - Spaghetti (162)	0.1353	4.0556	0.6387***	9.4902	7.4463***	13.3679
Ground and Whole Bean Coffee (401)	2.0189	2.2383	1.1933***	11.7109	0.0000	0.0000
Water - Bottled (382)	0.7620	1.2558	0.8979***	5.4826	0.0000	0.0000
Dairy Milk Refrigerated (123)	0.9394*	2.5306	1.0011***	8.8034	0.0000	0.0000
Detergents - Packaged (56)	0.8305	1.4470	1.0132***	5.1325	1.7222	0.9769
Soap - Liquid (120)	1.2486	1.4934	1.0758***	5.4450	0.0000	0.0000
Facial Tissues (43)	0.9681	0.8106	0.9499*	2.2098	0.0000	0.0000
Deodorants - Personal (201)	0.9696***	6.2405	0.9761***	25.0601	0.0000	0.0000
Dental Floss (62)	1.1961	1.3792	1.0585***	5.2400	0.0000	0.0000

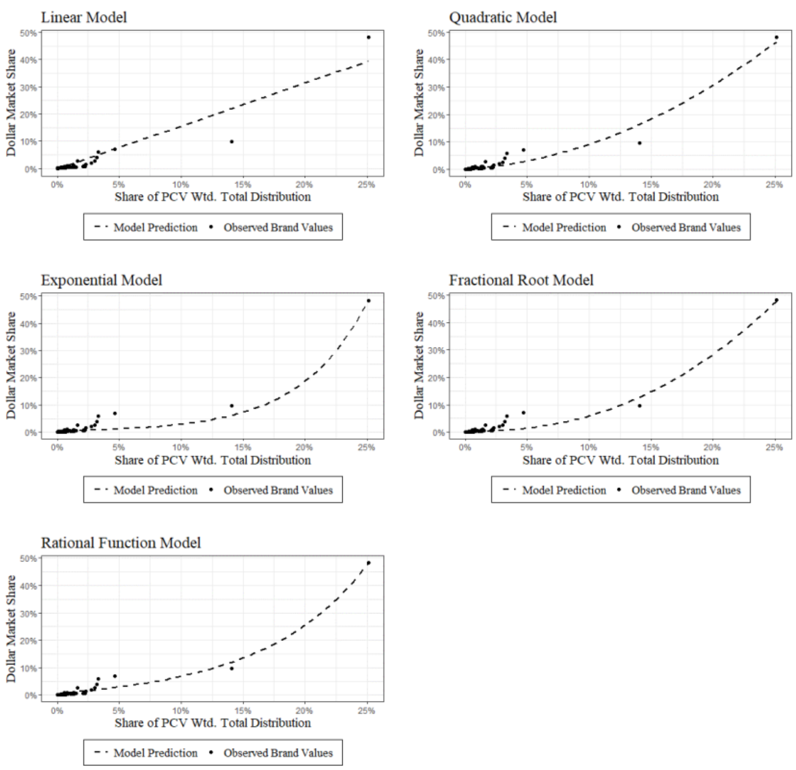
Note: *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$.

Appendix C: Model comparisons per category

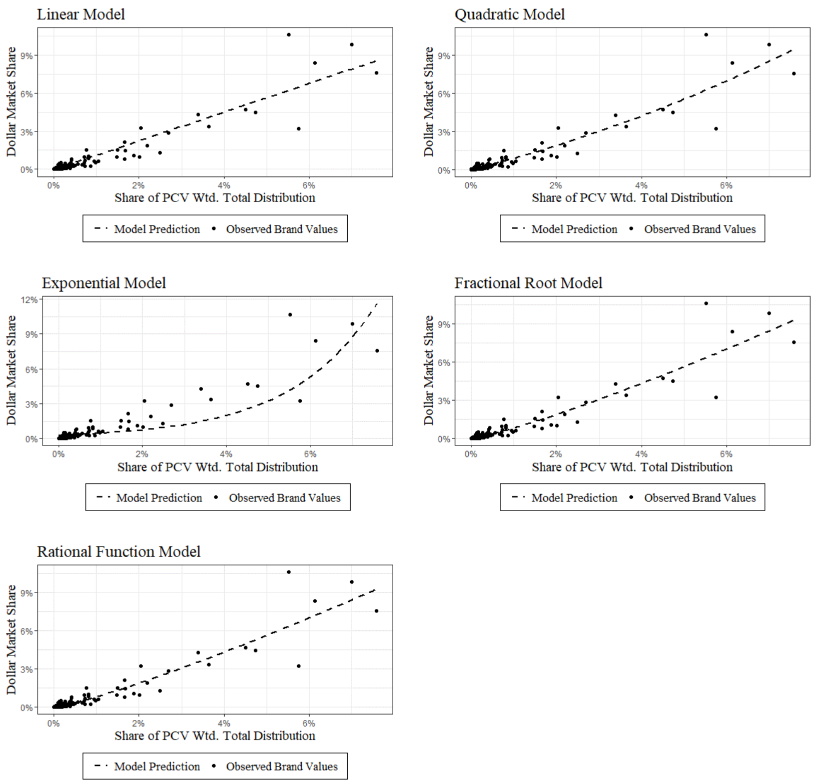
Potato Chips



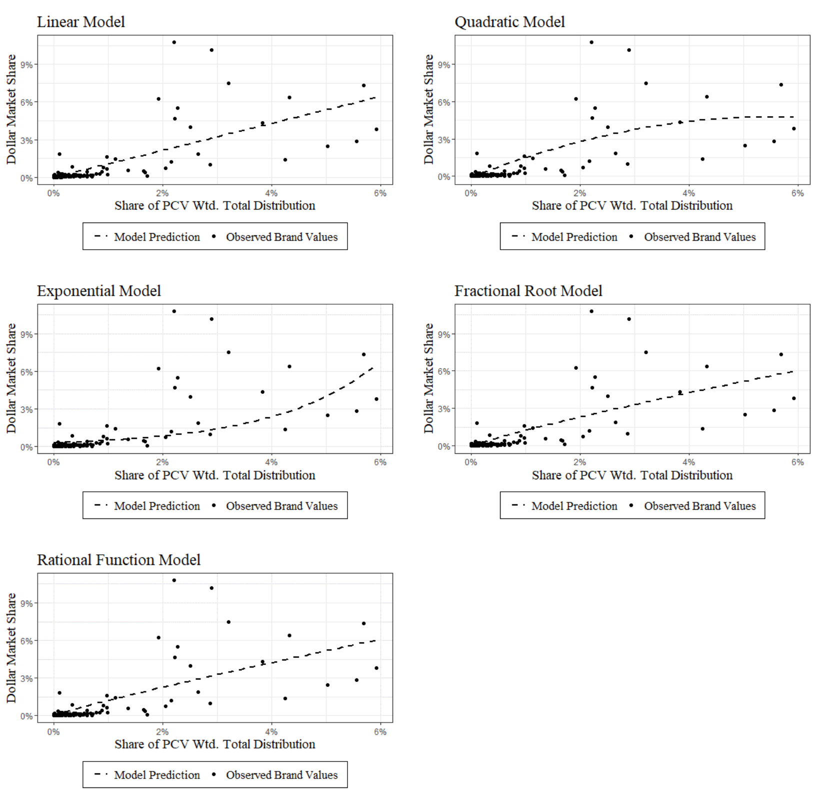
Pasta Spaghetti



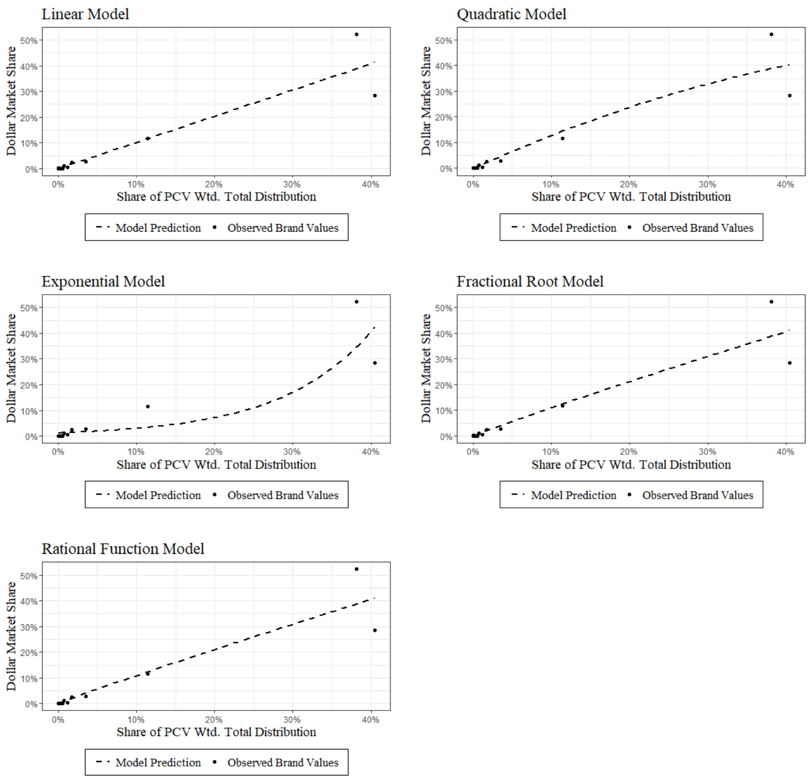
Ground and Whole Bean Coffee



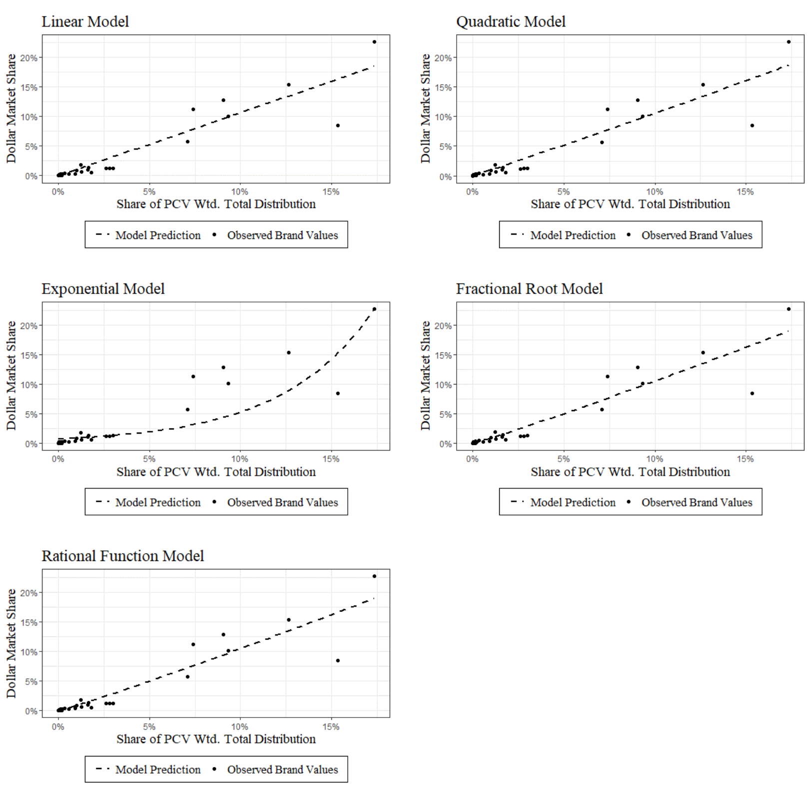
Water - Bottled



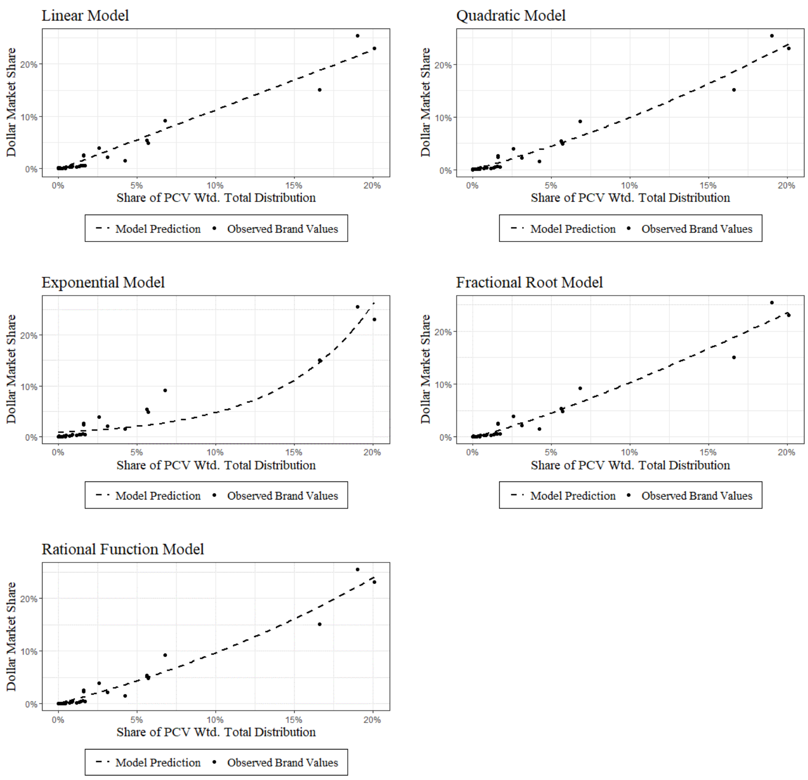
Facial Tissues



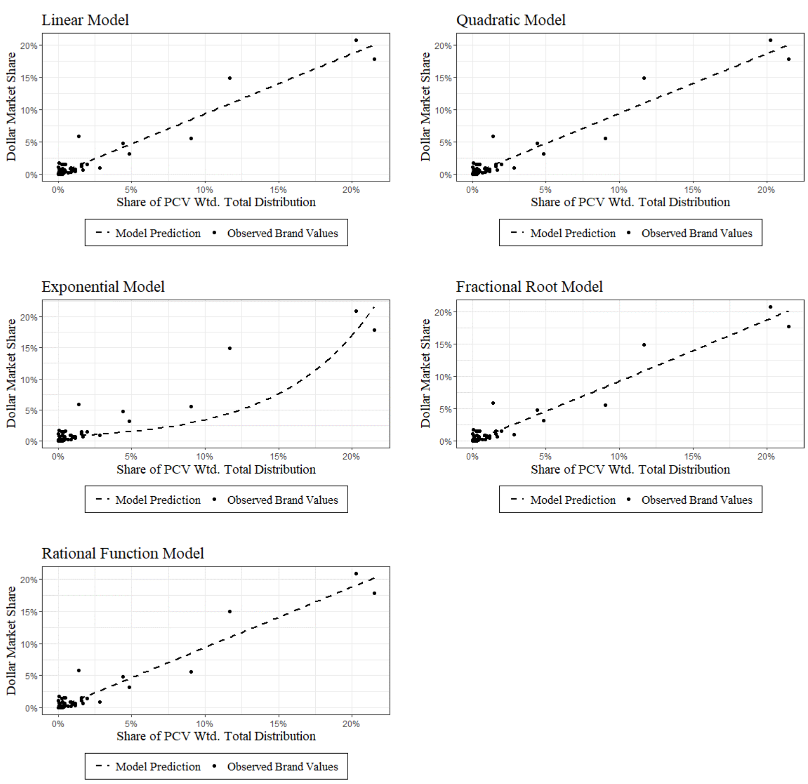
Soap - Liquid



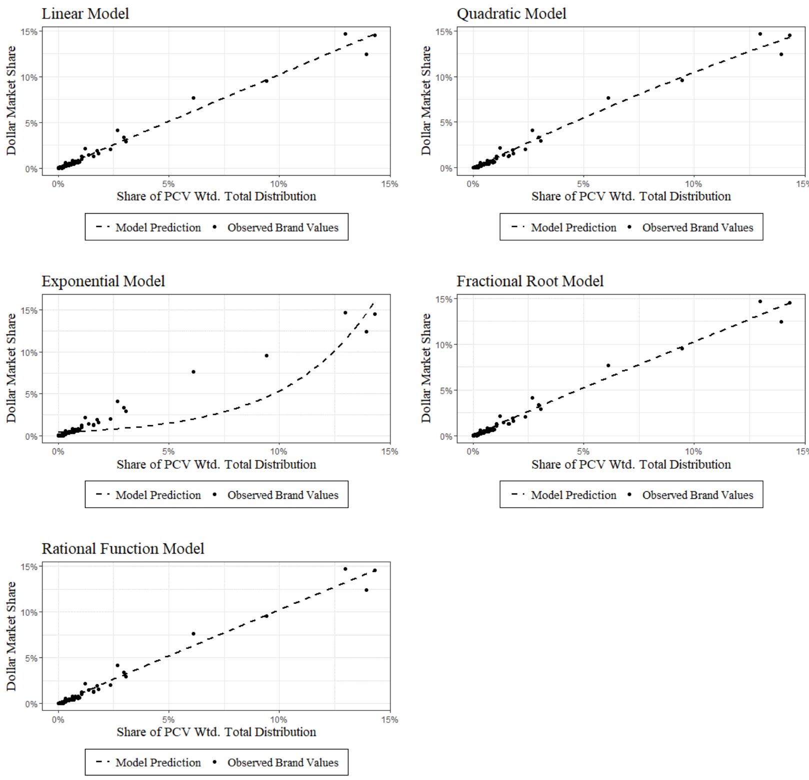
Detergents - Packaged



Dairy Milk Refrigerated



Deodorants - Personal



Dental Floss