What Drives Brands’ Pricing Clout and Receptivity? An Empirical Examination for the Chinese Packaged Goods Industry

bernadette van ewijk
university of amsterdam business school
Els Gijsbrechts
Tilburg University
Jan-Benedict E.M. Steenkamp
University of North Carolina at Chapel Hill

Acknowledgements:
We thank AiMark, Kantar Worldpanel, and the GfK Verein for providing the data. We gratefully acknowledge the comments of Yubo Chen, Angela Liu, Harald van Heerde, and Katrijn Gielens.

Cite as:
van ewijk bernadette, Gijsbrechts Els, Steenkamp Jan-Benedict E.M. (2021), What Drives Brands’ Pricing Clout and Receptivity? An Empirical Examination for the Chinese Packaged Goods Industry. *Proceedings of the European Marketing Academy*, 50th, (94692)

Paper from the 50th Annual EMAC Conference, Madrid, May 25-28, 2021

EMAC
EUROPEAN MARKETING ACADEMY

What Drives Brands' Pricing Clout and Receptivity?
An Empirical Examination for the Chinese Packaged Goods Industry

Abstract

As competition among CPG brands intensifies, brand managers increasingly focus on price. To what extent do price changes by brands affect (their own and competitive) sales (= clout)? To what extent are these brands vulnerable to price changes of competitors (= receptivity)? Which brand and category factors drive these outcomes? And: how can brands improve their position in this competitive landscape? The authors address these questions using a unique data set that combines five years of Chinese scanner panel, advertising, and survey data, across 377 brands in 50 categories. Social demonstrance reduces the intensity of price competition and makes brands less vulnerable to rival actions. Receptivity but especially clout tends to be lower for categories in the growth stage or with many players. Broadening distribution increases clout but also makes the brand more vulnerable to competitive price attacks, whereas increases in line length reduce receptivity to rival actions.

Key words: pricing, clout, receptivity
Track: Pricing & Promotions

1. Introduction

The competition between consumer packaged goods (CPG) brands is becoming more and more fierce, in both developed markets and emerging markets (McKinsey, 2018; Nielsen, 2019). In the battle for the customer, price is often the instrument of choice, because it can be adjusted by managers relatively quickly and easily (Leeflang & Wittink, 1996; Rao, Bergen, & Davis, 2000). Knowledge of a brand's competitive pricing power is critical for the development of a sound pricing strategy (Gijsbrechts, 1993).

However, the use of price as a competitive tool is not without danger and its consequences vary widely between brands. For one, brands differ in their price responsiveness (Ataman, van Heerde, & Mela, 2010; Bijmolt, van Heerde, & Pieters, 2005). Equally important, and relatively overlooked, is the asymmetry in *competitive* brand-price interdependencies. Apart from their ability to influence their own sales, brands also differ in their ability to affect the sales of other brands with their pricing moves – called 'clout' in the literature – and in the degree to which they are affected by other brands' pricing actions – referred to as 'receptivity' or 'vulnerability' (Cooper & Nakanishi, 1988; Kamakura & Russell, 1989). But why do some brands have more clout than other brands? And why are some brands more vulnerable to competitive pricing moves than others? The purpose of this article is to answer these questions.

Our contribution to the literature is twofold. First, to the best of our knowledge, we are the first to provide a comprehensive analysis of the drivers of clout and receptivity. We consider both brand factors and characteristics of the product category in which the brand operates. Our second contribution is the empirical context in which we investigate these drivers. The overwhelming body of research on pricing has been conducted in the U.S. and in Europe (Bijmolt et al., 2005; Cooper, 1988; Gordon, Goldfarb, & Li, 2013; Kamakura & Russell, 1989). Recently, various authors have called upon the field to expand marketing science's empirical lens to emerging markets (EMs) (Burgess & Steenkamp, 2006; Sheth, 2011; Sudhir et al., 2015). Our empirical context is the largest EM, viz., China.

We use a unique data set that combines five years of scanner panel (N=40,000), advertising, and survey data, across a broad set of 377 brands in over 50 CPG categories. We use these data to assess the brands' competitive price position, as reflected in their clout and receptivity. The insights we derive are particularly useful for managers to tailor their pricing approach to the (changing) category context, or to enhance their strategic position and turn their brands into 'competitive stars'. We document both the direction of the effects and their relative impact. Importantly, this impact differs for clout and receptivity, underscoring the need to consider both.

2. Research Framework

Building on Cooper (1988), we measure clout of brand j in category c as the sum of the squared own- and cross-elasticities of brand sales with respect to the brand's price change:

(1) $\mathrm{Clout}_{jc} = \sum_{ic} \left(\eta_{p_{jc}}^{s_{ic}}\right)^2$

where $\eta_{p_{jc}}^{s_{jc}}$ is brand j's own sales-price elasticity, i.e. the % change in its sales from a % change in its own price and $\eta_{p_{jc}}^{s_{ic}}$ is the cross-price elasticity of brand i's sales w.r.t. brand j's price.

The 'receptivity' of brand j in category c is measured as:

(2) $\mathrm{Recept}_{jc} = \sum_{ic} \left(\eta_{p_{ic}}^{s_{jc}}\right)^2$.

As indicated by Cooper & Nakanishi (1988, pp. 193-194), "Brands with high clout are more able to influence others, those with low clout pressure no others. Receptivity reflects the way brands are vulnerable to pressure from others. Brands with low receptivity are able to resist the advances of competitors." Together, these notions can be used to map the competitive price position of brands within a category – as shown in Figure 1[1].

Figure 1: Clout, Receptivity, and Brand Positioning

		Log(Clout)			
		Low	High		
Log(Receptivity)	High	Value brands (Category: asymmetric, mass at lower price-quality)	Mass brands (Category: perfect competition)	Low	Brand loyalty
	Low	Niche brands (Category: monopolistic competition)	Premium brands (Category: asymmetric, mass at higher price-quality)	High	
		Low	High		
		Brand appeal			

Brands in the lower-left quadrant (low clout; low receptivity) can be considered as '*niche*' brands that are relatively more insulated from competitors. While price changes by these brands are less effective in attracting customers from rivals (because of their low clout), their customer base tends to be loyal (because of their low receptivity), which makes them less vulnerable to competitive price moves (Bucklin, Russell, & Srinivasan, 1998). Brands in the lower-right quadrant (high clout; low receptivity) correspond with the profile of *'premium'* brands. As shown by Blattberg & Wisniewski (1989), price cuts can make these brands affordable to more customers and generate substantial sales shifts away from competitors. At the same time, the quality-oriented customer base of these brands tends to be loyal, i.e. not likely to respond to price moves by lower-quality competitors. The upper-left quadrant (low clout; high

[1] Because the distribution of clout and receptivity across brands tends to be skewed with long tails to the right, we will use the log of these metrics as dimensions in the map.

receptivity) is occupied by *'value'* brands, positioned at the low end of the price-quality spectrum. These brands only appeal to consumers willing to accept low quality. In line with Blattberg & Wisniewski (1989) and Bronnenberg & Wathieu (1996), price changes by these brands are less likely to attract consumers away from higher-quality brands whereas, conversely, their customers are quite willing to switch when those brands become affordable. Finally, brands in the upper-right quadrant (high clout; high receptivity) can be referred to as '*mass*' brands, subject to intense price competition with (all) other players in the category. These are typically mainstream brands whose customer base is willing to switch brands in response to competitive price changes.

We contend that brands' position in the map depends on the following brand characteristics: origin (i.e. foreign vs. domestic brand), line length (i.e. number of brand SKUs), price positioning (i.e. expensiveness relative to the category average), distribution intensity (i.e. availability at the top retailers), advertising intensity (i.e. share of voice in the category); and category characteristics: number of brands, social demonstrance (i.e extent to which use of brands as symbolic device to project and communicate the consumer's self-concept), local embeddedness (i.e. extent to which consumers believe category originates from China), stockpilability, stage in the product life cycle, and price reactions (i.e. extent to which brands in a category repond to each other's price changes). Table 1 summarizes our expectations regarding the effects on clout and receptivity.

Table 1: Summary of Expectations Effects Brand and Category Drivers on Clout and Receptivity

DRIVER	EXPECTED IMPACT	
	CLOUT	RECEPTIVITY
Brand origin	+	-
Brand line length	+	-
Brand price positioning	+	-
Brand distribution intensity	+	+
Brand advertising intensity	?	?
Category number of brands	?	?
Category social demonstrance	-	-
Category local embeddedness	?	?
Category stockpilability	+	+
Category stage of product life cycle	+	-
Category price reactions	-	+

3. Methodology

Our methodology consists of two stages. In the first stage, we obtain the own and cross price elasticities for each brand, using weekly time series for that brand. In the second stage, based on these price elasticities, we calculate clout and receptivity for each brand, and test the link with the brand and category drivers. Below, we discuss these stages in turn.

3.1 First Stage: Estimation of Brand-Price Elasticities and Cross-Elasticities

In this stage, we estimate a sales model for each separate brand:

$$\text{(3)}\quad \log s_{jct} = \beta_{0jc} + \beta_{1jc}\log \text{trend}_t + \beta_{2jc}\log s_{jct-1} + \beta_{3jc}\log p_{jct} + \beta_{4jc}\sum_{i,i\neq j}\log p_{ict} * m_{ic} + \sum_{i,i\neq j}\beta_{4jic}\log p_{ict} + \psi_{1jc}\log PD_{jct} + \psi_{2jc}a_{jt} + \psi_{3jc}\log d_{jct} + \psi_{4jc}\log l_{jct} + \sum_k \varphi_{kjc}\,\text{copula}_{kjct} + \gamma_{1jc}\sin\left(\frac{2\pi t}{52}\right) + \gamma_{2jc}\cos\left(\frac{2\pi t}{52}\right) + \gamma_{3jc}\text{pre NY}_t + \gamma_{4jc}\text{NY}_t + \gamma_{5jc}\text{post NY}_t + \varepsilon_{jct}$$

where i and j are brand indicators and c is a category indicator; s_{jct} are the volume market sales of brand j in category c in week t; m_{ic} is brand i's market share); p_{jct}, a_{jct}, d_{jct}, l_{jct} are the brand's price, advertising, distribution and line length, respectively; $\sin\left(\frac{2\pi t}{52}\right)$ and $\cos\left(\frac{2\pi t}{52}\right)$ are trigonometric terms to control for seasonality; pre NY_t, NY_t and post NY_t are dummy variables that equal 1 in the week preceding, equal to, and following Chinese new year, respectively (and zero otherwise); $PD_{jct}$is the brand's weekly price dispersion; copula_{kjct} is the brand's Gaussian copula for marketing mix variable k (see below); and ε_{jct} are normally-distributed error terms. Possible endogeneity for advertising, distribution, and line length is addressed through the Gaussian copula method (Park & Gupta, 2012), while for price, we set up separate price equations for each brand, which we estimate along with the sales as a 'structured' system of equations, allowing the errors to be correlated (see Ataman et al., 2010; van Heerde, Gijsbrechts, & Pauwels, 2015 for a similar approach). We use the model estimates to obtain clout and receptivity for each brand.

3.2 Second Stage: Estimation of the Impact of Brand- and Category Factors

Next, we examine what drives the differences in clout and receptivity across categories and brands. We 'stack' clout and receptivity across all brands, and use them as dependent variables in a second-stage regression (using WLS) with brand- and category-characteristics as regressors:

$$\text{(4)}\quad \log(\text{Clout}_{jc}) = \delta_o + \delta_1 or_{jc} + \delta_2 li_{jc} + \delta_3 pp_{jc} + \delta_4 di_{jc} + \delta_5 ai_{jc} + \delta_6 nr_c + \delta_7 sd_c + \delta_8 le_c + \delta_9 st_c + \delta_{10} lc_c + \delta_{11} pr_c + \sum_l \delta_{12,l}\,\text{Type}_{l,c} + e_{jc}$$

$$\text{(5)}\quad \log(\text{Recept}_{jc}) = \kappa_o + \kappa_1 or_{jc} + \kappa_2 li_{jc} + \kappa_3 pp_{jc} + \kappa_4 di_{jc} + \kappa_5 ai_{jc} + \kappa_6 nr_c + \kappa_7 sd_c + \kappa_8 le_c + \kappa_9 st_c + \kappa_{10} lc_c + \kappa_{11} pr_c + \sum_l \kappa_{12,l}\,\text{Type}_{l,c} + r_{jc}$$

where or_{jc} indicates whether brand j's origin is foreign (1) vs. local (-1); li_{jc}, pp_{jc} , di_{jc} and ai_{jc} are the line length index, price positioning relative to competitors, distribution and advertising intensity of brand j, respectively, nr_c captures the number of brands in the category to which brand j belongs; sd_c, le_c, st_c, lc_c, and pr_c are the social-demonstrance level, local embeddedness, stockpilability, product life cycle stage, and level of price reactions in that category; $Type_{l,c}$ indicates category type; and e_{jc} is a random component.

We test our framework of drivers of brand clout and receptivity using data for the period 2011 and 2015 from a Chinese urban household panel (n=40,000) operated by Kantar Worldpanel. 377 brands in 50 categories were selected for which the clout and receptivity were be estimated. To assess the category characteristics, we combined responses to a survey administered by GfK in 2014 among urban Chinese consumers, with responses to a survey among experts. Advertising spending data were obtained from Kantar Media.

4. Findings

4.1 First-Stage Results

Following Figure 1, we look at how the brands are distributed in the $\log(Clout_{jc})$ X $\log(Recept_{jc})$ space. About one third of the brands are classified as '*niche*' brands (low clout; low receptivity, e.g., Savol in hair conditioning products). The group that consists of '*premium*' brands (high clout; low receptivity) is much smaller (e.g., Huggies in diapers). The group of '*value*' brands (low clout; high receptivity) has the same size (e.g., Hygienix in toilet tissues). '*Mass*' brands (high clout; high receptivity) constitute a large group (e.g., Lion in toothbrushes). An example of a more powerful brand includes Nestlé in instant coffee (situated in the '*premium*' quadrant), while Shinho in cooking sauces is an example of a less powerful brand (situated in the '*value*' quadrant). We now turn to what drives these differences in clout and vulnerability.

4.2 Second-Stage Results

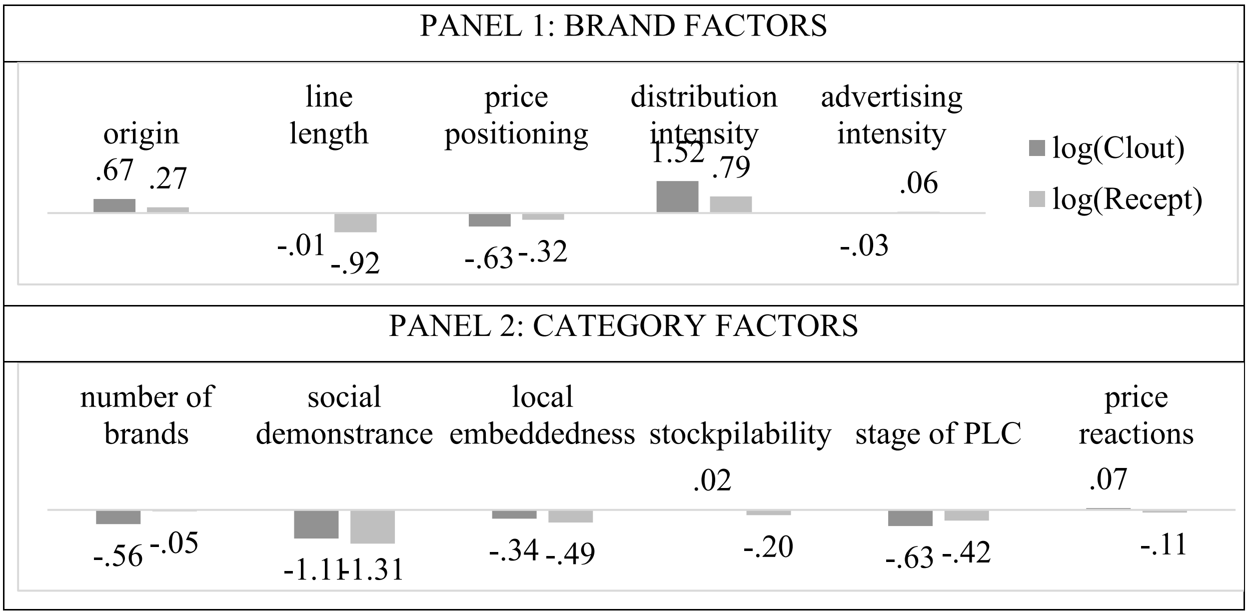
Table 2 shows the results of the second-stage analyses and reveals that brand and category drivers systematically affect the clout and receptivity of a brand. To conserve space, we do not discuss these parameter estimates, but calculate effect sizes by comparing the clout vs. receptivity for each driver at its 10^{th} percentile level vs. its 90^{th} percentile level (except for the dummy brand origin where we compare foreign vs. local), keeping all other variables at their average level. Figure 2 displays the results.

Table 2: Results of Second-Stage Analysis

VARIABLE	ESTIMATE (TWO-SIDED P-VALUE)	
	$\log(Clout_{jc})$	$\log(Recept_{jc})$
Intercept	5.30 (.001)	8.04 (<.0001)
Brand origin: foreign (or_{jc})	.34 (<.0001)	.13 (.10)
Brand line length index (li_{jc})	-.007 (.95)	-.45 (<.0001)
Brand price positioning (pp_{jc})	-.63 (.0004)	-.31 (.07)
Brand distribution intensity (di_{jc})	3.16 (<.0001)	1.65 (.007)
Brand advertising intensity $\log(ai_{jc})^d$	-.0007 (.90)	.001 (.77)
Category number of brands (nr_c)	-.09 (.03)	-.008 (.84)
Category social demonstrance (sd_c)	-1.32 (<.0001)	-1.55 (<.0001)
Category local embeddedness (le_c)	-.11 (.92)	-.15 (.03)
Category stockpilability (st_c)	.01 (.92)	-.12 (.26)
Category product life cycle stage (lc_c)	-3.71 (.004)	-2.48 (.06)
Category price reactions $\log(pr_c)$	.02 (.75)	-.03 (.61)
Category type: beverages ($Type_{1c}$)	.54 (<.0001)	.79 (<.0001)
Category type: personal care ($Type_{2c}$)	-.25 (.03)	-.27 (.07)
Category type: household care ($Type_{3c}$)	-.43 (<.004)	-.17 (.14)

Note: R^2 (adjusted) for $\log(Clout_{jc})$ vs. $\log(Recept_{jc})$:.35 (.32) vs. .33 (.31); local brands and food categories are reference groups.

Figure 2: Relative Impact of Different Drivers



Distribution is the brand factor that has the strongest impact, increasing both clout and receptivity. Because the former effect outweighs the latter, distribution enhances pricing power. Line length, too, substantially enhances brand power, but through a very different mechanism: by making the brand less vulnerable to competitive price moves. Price position and brand origin are equally important, but produce an opposite pattern of effects. Premium-priced brands show modest reductions in clout and receptivity. Because the former is larger than the latter, it follows that high-priced brands have somewhat lower power. The effect of brand origin (foreign brands) is higher on clout than on receptivity. Hence, foreign brands have more pricing power than local brands. The role of advertising spending is negligible.

Among the category factors, social demonstrance is the dominant driver, reducing brands' clout and receptivity. Category growth and number of players drive down brands' ability to affect rivals, whereas growth and local embeddedness shield them against competitor moves. Stockpilability and competitive price reactions play only a minor role.

5. Conclusions, Implications and Limitations

To the best of our knowledge, our study is the first large scale study into the competitive price position of CPG brands in China, by considering both their clout and receptivity, and uncovering brand and category factors that drive these metrics.

In assessing the role of brand prices, we consider clout and receptivity in combination. This is important for two reasons. First, together, these metrics are indicative of a brand's performance potential. Previous papers have often associated high clout with brand strength (Blattberg & Wisniewski, 1989; Cooper, 1988; Ilfeld & Winer, 2002; Russell, 1992; Russell & Kamakura, 1994) and the potential to achieve higher profit (Barney, 1991; Gázquez-Abad & Martínez-López, 2016). However, as indicated by Mela et al. (1998), high clout in itself is not always a good thing. The combination of high clout and high receptivity suggests low distinctiveness and high substitutability. When high clout goes along with low receptivity, the impact of their pricing actions on rivals is stronger than the reverse, brands in this quadrant are typically 'power' brands that enjoy high equity and market leadership (Chintagunta, 2002; Desai, Gauri, & Ma, 2014; Kim, Albuquerque, & Bronnenberg, 2017; Shankar, 2006). Second, clout and receptivity are useful to guide firms' strategic actions. While clout indicates to what extent the brand's price moves can enhance sales at the expense of rivals, receptivity offers a lens on the consequences of competitors' eventual reactions to those moves. Managers need to assess their position along both dimensions, and adjust their pricing approach accordingly. Social demonstrance reduces the intensity of price competition in the category and makes brands less vulnerable to rival actions. Conversely, receptivity but especially clout tends to be lower for categories in the growth stage or with many players – rendering price less appealing as the instrument-of-choice. Broadening the brand's distribution substantially enhances its clout, but also makes it more vulnerable to rival price moves. Conversely, while increasing line length does not affect the brand's own price response, it does significantly reduce its receptivity to rival price actions, thereby substantially increasing the brands' pricing power. High-end price positioning decreases clout more than receptivity, whereas advertising investments have little impact altogether.

Our study has limitations that offer opportunities for future research. First, our empirical analysis only pertains to China. Though our conceptualization is more general, our findings should be verified with primary research in other DM and EM countries. Second, our empirical context is the CPG industry. It remains to be tested whether our findings also hold for big-ticket durables in China, or more generally in other countries. Third, the panel covers urban households, not those in rural areas. We note that these consumers represent the bulk of the Chinese market: only 25% of China's GDP comes from rural households (China Daily, 2015). Still, this segment may gain importance in the future, making it worthwhile to study brand-price competition in rural regions. Finally, like previous large-scale studies, we documented market-level price response, which made it feasible to cover a large number of brands and categories. Though we verified our results for different city tier types, it may be useful to study price reactions at the household level – something we leave for future analysis.

References

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

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bijmolt, T. H. A., van Heerde, H. J., & Pieters, R. G. M. (2005). New Empirical Generalizations on the Determinants of Price Elasticity. *Journal of Marketing Research*, *42*(2), 141–156. https://doi.org/10.1509/jmkr.42.2.141.62296

Blattberg, R. C., & Wisniewski, K. J. (1989). Price-Induced Patterns of Competition. *Marketing Science*, *8*(4), 291–309. https://doi.org/https://doi.org/10.1287/mksc.8.4.291

Bucklin, R. E., Russell, G. J., & Srinivasan, V. (1998). A Relationship between Market Share Elasticities and Brand Switching Probabilities. *Journal of Marketing Research*, *35*(1), 99–113. https://doi.org/10.2307/3151933

Burgess, S. M., & Steenkamp, J.-B. E. M. (2006). Marketing Renaissance: How Research in Emerging Markets Advances Marketing Science and Practice. *International Journal of Research in Marketing*, *23*(4), 337–356. https://doi.org/10.1016/j.ijresmar.2006.08.001

China Daily. (2015). Rural-Urban Income Gap Narrows. Retrieved June 6, 2019, from http://www.chinadaily.com.cn/

Chintagunta, P. K. (2002). Investigating Category Pricing Behavior at a Retail Chain. *Journal of Marketing Research*, *39*(2), 141–154. https://doi.org/10.1509/jmkr.39.2.141.19090

Cooper, L. G. (1988). Competitive Maps: The Structure Underlying Asymmetric Cross Elasticities. *Management Science*, *34*(6), 707–723. https://doi.org/10.1287/mnsc.34.6.707

Cooper, L. G., & Nakanishi, M. (1988). *Market-Share Analysis*. Boston, MA: Kluwer Academic Publishers.

Desai, K. K., Gauri, D. K., & Ma, Y. (2014). An Empirical Investigation of Composite Product Choice. *Journal of Retailing*, *90*(4), 493–510. https://doi.org/10.1016/j.jretai.2014.09.002

Gázquez-Abad, J. C., & Martínez-López, F. J. (2016). Increasing A Brand's Competitive Clout: The Role of Market Share, Consumer Preference, and Price Sensitivity. *Journal of Marketing Management*, *32*(1–2), 71–99. https://doi.org/10.1080/0267257X.2015.1089307

Gijsbrechts, E. (1993). Prices and Pricing Research in Consumer Marketing: Some Recent Developments. *International Journal of Research in Marketing*, *10*(2), 115–151.

https://doi.org/10.1016/0167-8116(93)90001-F
Gordon, B. R., Goldfarb, A., & Li, Y. (2013). Does Price Elasticity Vary with Economic Growth? A Cross-Category Analysis. *Journal of Marketing Research*, *50*(1), 4–23. https://doi.org/10.1509/jmr.11.0162
Ilfeld, J. S., & Winer, R. S. (2002). Generating Website Traffic. *Journal of Advertising Research*, *42*(5), 49–61. https://doi.org/10.2501/JAR-42-5-49-61
Kamakura, W. A., & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research*, *26*(4), 379–390. https://doi.org/10.2307/3172759
Kim, J. B., Albuquerque, P., & Bronnenberg, B. J. (2017). The Probit Choice Model Under Sequential Search with an Application to Online Retailing. *Management Science*, *63*(11), 3911–3929. https://doi.org/10.1287/mnsc.2016.2545
Leeflang, P. S. H., & Wittink, D. R. (1996). Competitive Reaction Versus Consumer Response: Do Managers Overreact? *International Journal of Research in Marketing*, *13*(2), 103–119. https://doi.org/10.1016/0167-8116(96)00003-1
McKinsey. (2018). *Commercial Excellence in China: Lessons From the top CPG Companies*. Retrieved from https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/commercial-excellence-in-china-lessons-from-the-top-cpg-companies
Nielsen. (2019). *Understanding Your Competitive CPG Landscape*.
Park, S., & Gupta, S. (2012). Handling Endogenous Regressors by Joint Estimation Using Copulas. *Marketing Science*, *31*(4), 567–586. https://doi.org/10.1287/mksc.1120.0718
Rao, A. R., Bergen, M. E., & Davis, S. (2000). How to Fight A Price War. *Harvard Business Review*, *78*(2), 107–117.
Russell, G. J. (1992). A Model of Latent Symmetry in Cross Price Elasticities. *Marketing Letters*, *3*(2), 157–169. https://doi.org/10.1007/BF00993995
Russell, G. J., & Kamakura, W. A. (1994). Understanding Brand Competition Using Micro and Macro Scanner Data. *Journal of Marketing Research*, *31*(2), 289–303. https://doi.org/10.2307/3152200
Shankar, V. (2006). Proactive and Reactive Prouct Line Strategies: Asymmetries Between Market Leaders and Followers. *Management Science*, *52*(2), 276–292. https://doi.org/10.1287/mnsc.1050.0443
Sheth, J. N. (2011). Impact of Emerging Markets on Marketing: Rethinking Existing Perspectives and Practices. *Journal of Marketing*, *75*(4), 166–182. https://doi.org/10.1509/jmkg.75.4.166
Sudhir, K., Priester, J., Shum, M., Atkin, D., Foster, A., Iyer, G., … Wood, W. (2015). Research Opportunities in Emerging Markets: An Inter-disciplinary Perspective from Marketing, Economics, and Psychology. *Customer Needs and Solutions*, *2*(4), 264–276. https://doi.org/10.1007/s40547-015-0044-1
van Heerde, H. J., Gijsbrechts, E., & Pauwels, K. H. (2015). Fanning the Flames? How Media Coverage of a Price War Affects Retailers, Consumers, and Investors. *Journal of Marketing Research*, *52*(5), 674–693. https://doi.org/10.1509/jmr.13.0260