

Editorial

Empirical Generalizations in Retailing

Introduction

Retailing is a complex arena, involving multiple phenomena including location selection, pricing and promotions, distribution, market response, lifetime value of retail customers, merchandising, customer loyalty programs, private labels, price matching and return policies, new products, e-tailing, retailer–manufacturer interactions, product assortment and stock-outs, retail branding, and customer satisfaction. Both marketing scholars and practitioners have devoted considerable effort to researching these topics, primarily in “one-off” studies. However, decisions in these areas greatly benefit from empirical generalizations. This, combined with managers with an analytics orientation at many organizations, has provided a great opportunity for academics in retailing research to have an impact on marketing practice.

Some of the best known empirical generalizations in Marketing concern Retailing. One of these early empirical generalizations is Reilly’s (1931) Law of Retail Gravitation, empirically verified by Converse (1949) and implemented into a probabilistic model by Huff (1964), which can be viewed as a precursor to the widely used discrete choice models (McFadden 1981). Another earlier empirical generalization, which is still relevant today, is the Wheel of Retailing proposed by McNair (1958) and empirically tested by Hollander (1960).

One major endeavor to compile research focused on empirical generalizations in marketing occurred 20 years ago (Bass and Wind 1995). Similarly, the MSI monograph edited by Hanssens (2009) is focused on marketing in general rather than retailing. This special issue on “Empirical Generalizations in Retailing” aims to provide a cohesive view of different aspects of retailing and to bridge the gap between theory and practice by nudging retail managers towards a more empirical perspective in their retail decisions at both strategic and tactical levels. The topics covered in this special issue include private labels and store brand share, semantic cues, shelf space elasticity, distribution, loss aversion, search engine advertising, offline information search, e-word of mouth, socially responsible products, switching costs, and the accuracy of scanned prices.

How are empirical generalizations related to theory development? The relation between theory and data is thought of in many multiple which vary in the primacy of emphasis on theory versus data. These form a continuum as depicted below.

Role of theory	Role of data
Theory as religion	Irrelevant
Theory testing	Data generated to see if it is consistent with the theory
Theory exploration	Relevant data collected and related to multiple (competing theories)
Theory and data integration	Iterative analysis of theory and data
Theory inspiration/development	Data examined for explanations (theories)
Atheoretical exploration	Data described

Empirical generalizations, and their development via meta-analysis, are relevant to all of the roles of theory except religion, which rejects the relevance of data. For example, grouping related studies (replications) can provide a more powerful test of specific theories than any single study as well as help identify boundary conditions for them. Toward the other end of the spectrum, examination of data patterns (e.g., via machine learning) can reveal empirical regularities which can then be recast as theories. Many marketing scholars view science as “prescriptive,” “analytical,” and “normative.” We argue, on the contrary, that science is also highly exploratory and empirical; one can (or at least should) only be “prescriptive, analytical and normative” after a “theory” or a view of the world has been empirically tested and validated. Empirical generalizations are important for both discovery (theory generation) and evaluation (theory testing and calibration). In other words, theory and empirical analysis are like chicken and eggs; neither exists without the other and continuous iteration between the two leads to development.

Papers in Special Issue on “Empirical Generalizations in Retailing”

In developing this special issue, we received 37 submissions, twelve of which were accepted for publication. Two of the papers

relate to private labels. One (“Taking private labels upmarket: Empirical generalizations on category drivers of premium private label introductions” by ter Braak, Geyskens, Dekimpe) generalizes across approximately 150 categories for six retailers from two countries. The authors find that retailers are more likely to introduce premium PLs in categories with a higher industry PL share, and with a more proliferated assortment in terms of standard PLs. The other (“Determinants of Store Brand Share” by Sethuraman and Gielens), uses a large data set that combines prices and market share information for national brands and PLs on 40 product categories across nine different retailers during a 4 year period, and finds that private labels’ market power is mostly influenced by category idiosyncrasies rather than retailers’ market power.

The paper on “Distribution and Market Share” (by Wilbur and Farris) analyzes more than 79,000 stock-keeping units (SKUs) in 37 consumer packaged goods categories totaling \$55 billion in annual revenue. It shows that, in 86% of product categories, the relationship between market share and retail distribution is increasing and convex at the SKU level.

The relation of sales to space allocated to a product in retail settings is studied in “Shelf Space Elasticity: A Meta-Analysis” (by Eisend). The average observed shelf space elasticity is .17, and varies across product categories, with the lowest estimates found for commodities, followed by staples, and the highest estimates for impulse buys. Increases in shelf space result in greater changes in sales than shelf space reduction, a finding that emphasizes the importance of shelf space as a marketing tool.

“A Meta-Analysis of Loss Aversion in Product Choice” (by Neumann and Böckenholt) draws empirical generalizations from 33 studies (providing 109 observations) investigating loss aversion in random utility models of brand choice. Specifically, it uses multilevel modeling techniques to examine potential moderators of preference asymmetries as well as the variability of loss-aversion effects within and across studies. It finds that loss aversion is evident in product choice, but that it varies substantially across contexts.

In a behavioral paper (“The Contingent Effects of Semantic Price Cues” by Grewal, Roggeveen, and Lindsey-Mullikin), the meta-analysis demonstrates the robustness of differential effects of semantic cues, and indicate that a within-store cue (compared to a between store cue) enhances evaluations when shopping in a store with a utilitarian goal, when shopping alone, and when shoppers motivation to process information is low.

Related to the online world, in “Empirical Generalizations in Search Engine Advertising”, Nabou, Lilienthal, and Skiera analyze and compare advertising effectiveness across industries, and decompose the effect of increases in SEA expenditures on prices per click (price effect) and number of clicks (quantity effect). A cross-country, cross-industry study shows that 44% of the increase in SEA expenditures is associated with more clicks and 56% with higher prices. Further, in “How Online Product Reviews Affect Retail Sales,” Floyd, Freling, Alhoqail, Cho, and Freling conduct a meta-analysis of 26 empirical studies that yield 443 sales elasticities to examine the impact of online reviews on sales.

“The Antecedents and Moderators of Offline Information Search: A Meta-Analysis,” (by Maity, Dass, and Malhotra) shows that the effects of several antecedents (cost, price dispersion, knowledge, prior experience) on offline information search vary substantially in terms of signs and magnitudes. In addition, the paper shows that inverted-U shaped relationships between many of the antecedent variables and information search appear to exist.

In “The Role of the Beneficiary in Willingness to Pay for Socially Responsible Products: A Meta-Analysis,” Tully and Winer find that the average premium is 16.6%, and that, on average, 60% of respondents are willing to pay a positive premium. Willingness to pay is greater for goods where the socially responsible element benefits humans (e.g., labor practices) compared to those that benefit the environment.

“The Impact of Service Characteristics On Switching Costs” (by Blut, Beatty, Evanschitzky, and Brock), carries out a meta-analytic review of the literature on the switching costs-customer loyalty link using a hierarchical linear model and a sample of 1,694 customers from 51 service industries. The results suggest that external switching costs have a stronger average effect on customer loyalty than do internal switching costs.

“The Accuracy of Scanned Prices,” (by Hardesty, Goodstein, Grewal, Miyazaki, and Kopalle) analyzes a longitudinal price scanner data from 1996 to 2010, with 231,760 products screened over a 15-year period. It finds that though error rates have improved over the years, retailers would be well-advised to scrutinize the accuracy of their scanned prices more carefully as the rate of errors still far exceeds the FTC standard of 2% and industry standard of .70%.

The future

Empirical generalizations are inherently backwards looking. The implicit assumption that things stay the same (i.e., the past predicts the future) is a reasonable starting point. However, things do change. For example, different meta-analyses of price elasticity have produced different results (Bijmolt, van Heerde, and Pieters 2005; Sethuraman, Srinivasan, and Kim 1999; Tellis 1988) as have analyses of advertising elasticities (Assmus, Farley, and Lehmann 1984; Sethuraman, Tellis, and Briesch 2011). This suggests that it is important to periodically repeat analyses and incorporate more recent results. Additionally, incorporating time as an independent variable (determinant) in meta analyses is a worthwhile way to capture trends which can then be projected into the future (with limited confidence).

Beyond re-examining specific generalizations, in the future it will be productive to examine other (emerging) topics. These include obvious ones related to online behavior, channel coordination (and competition), and social influence. Importantly, other emerging topics which will need empirical generalizations include multi-channel and electronic retailing, data driven retailing to improve profitability and shareholder value, how best to structure the data analytic function in a retailing organization, transactions and payment methods, and the delivery approaches.

Progress in developing generalizations will require a change in perspective. The current model for academic publication,

often driven by the review process, is that each paper should be, or at least be close to, “perfect” in terms of both use of (advanced) methods and being theory driven. Unfortunately, this is illogical (nothing produced by humans is ever perfect) and limiting (i.e., it ignores the fact that data exploration can lead to theory development). What is needed is the recognition that generalizations (i.e., true knowledge) can only emerge after multiple researchers “triangulate” findings using multiple methods and data sets and, explore boundary conditions, mediators, and moderators via both independent study and conceptual replications (exact replications are essentially impossible given changes over time, etc.) Viewed this way, many “imperfections” (vs. unacceptable sloppiness) provide the basis for understanding just how generalizable a generalization is.

Additionally, focus should center on how big an effect is (e.g., an elasticity) rather than on how significant a result is. Significance is largely a function of the consistency of a result across observations and sample size rather than how large the (average) effect is. Correlations combine both the size of an effect and its consistency. By contrast, regression coefficients (elasticities) assess the (average) magnitude of an effect. For most practical applications, it is the latter on which decisions are most productively based.

How can a manager use an empirical generalization? The most obvious way is to assume that the generalization (appropriately adjusted to account for the particular situation, i.e., based on a multiple regression versus a simple mean) holds and optimize decisions accordingly. A more sophisticated form of this is to allow for variation in the generalization (e.g., elasticity) and explore optimal decisions for different levels (e.g., pessimistic, best guess, optimistic) of the generalization/elasticity.

A less obvious, but effective use of empirical generalizations, is as a control/check on plans. For example, marketing and new business plans typically specify both specific decisions (e.g., price, advertising) and expected outcomes. This combination implies one or more elasticities. A wise use of generalizations is to see if the implicit elasticity is within or outside the range found in the analysis/generalization. While it is possible to have exceptional results, implicitly assuming advertising elasticity is 0.8 (versus, say, .03) or price elasticity is -5.0 (versus, say, -2.5) should at least raise questions about “what makes your advertising or price so special?”

Thanks

We had a great team of reviewers who helped us with the special issue on “Empirical Generalizations in Retailing” at the *Journal of Retailing*. The Editors of the *Journal of Retailing* and the three Co-Editors of this special issue would like to express their sincere appreciation to the reviewers who provided expert advice with respect to the manuscripts submitted for possible publication in this special issue. Their time and effort were instrumental in the development of this special issue. Of course, the main thanks goes to the authors for their efforts in producing the papers in this issue.

Reviewers:

Kusum	Ailawadi	Dartmouth College
Mark	Alpert	University of Texas (Austin)
Neeraj	Arora	University of Wisconsin (Madison)
Abhijit	Biswas	Wayne State University
Sharad	Borle	Rice University
Doug	Bowman	Emory University
Alan	Collins	University College Cork
Joseph	Cronin	Florida State University
Marnik	Dekimpe	Tilburg University
Devon	DelVecchio	Miami University
Ramarao	Desiraju	University of Central Florida
Sri	Devi Duvvuri	University at Buffalo
Yaniv	Dover	Dartmouth College
Raj	Echambadi	University of Illinois (Urbana–Champagne)
Martin	Eisend	European University Viadrina
Hooman	Estelami	Fordham University
Paul	Farris	University of Virginia
George	Franke	University of Alabama
Dinesh	Gauri	Syracuse University
Avi	Goldfarb	University of Toronto
Ronald	Goodstein	Georgetown University
Dhruv	Grewal	Babson College
Bruce	Hardie	London Business School
Sam	Hui	New York University
Chuck	Ingene	University of Mississippi
Carol	Kaufman-Scarborough	Rutgers University
Roger	Kerin	Southern Methodist University
V.	Kumar	Georgia State University
Jeffrey	Larson	Brigham Young University
Leonard	Lee	Columbia University
Yu	Ma	University of Alberta
Vikas	Mittal	Rice University
Yesim	Orhun	University of Michigan
Koen	Pauwels	Özyeğin University
Priya	Raghubir	New York University
Brian	Ratchford	University of Texas (Dallas)
Ruby	Roy Dholakia	University of Rhode Island
Gary	Russell	University of Iowa
Oliver	Rutz	University of Washington
Sanjit	Sengupta	San Francisco State University
Raj	Sethuraman	Southern Methodist University
Venky	Shankar	Texas A&M University
Sivaramakrishnan	Siddharth	University of Southern California
Vishal	Singh	New York University
Bernd	Skiera	Goethe University
Shrihari	Sridhar	Penn State University
Raji	Srinivasan	University of Texas (Austin)
Shuba	Srinivasan	Boston University
Baohong	Sun	Cheung Kong Graduate School of Business
Yacheng	Sun	University of Colorado
Rajneesh	Suri	Drexel University
Debabrata	Talukdar	University at Buffalo
Sudhir	Voleti	Indian School of Business
Barton	Weitz	University of Florida
Kenneth	Wilbur	University of California (San Diego)
Manjit	Yadav	Texas A&M University
Jie	Zhang	University of Maryland
Ying	Zhao	HKUST

References

- Assmus, Gert, John U. Farley and Donald R. Lehmann (1984), "How advertising affects sales: meta-analysis of econometric results," *Journal of Marketing Research*, 21 (1), 65–74.
- Bass, Frank M. and Jerry Wind (1995), "Introduction to the special issue: empirical generalizations in marketing," *Marketing Science*, 14 (3 Suppl.), G1–5.
- Bijmolt, Tammo H., Harald J. van Heerde and Rik G.M. Pieters (2005), "New empirical generalizations on the determinants of price elasticity," *Journal of Marketing Research*, 42 (2), 141–56.
- Converse, Paul D. (1949), "New laws of retail gravitation," *Journal of Marketing*, 14 (3), 379–84.
- Hanssens, Dominique M. (2009), *Empirical Generalizations about Marketing Impact*, Marketing Science Institute, Relevant Knowledge Series.
- Hollander, Stanley C. (1960), "The wheel of retailing," *Journal of Marketing*, 25 (1), 37–42.
- Huff, David L. (1964), "Defining and estimating a trading area," *Journal of Marketing*, 28 (3), 34–8.
- McFadden, Daniel (1981), "Econometric models of probabilistic choice," in *Structural Analysis of Discrete Data*, Manski C. and McFadden D., eds. Cambridge, MA: MIT Press, 198–272.
- McNair, M.P. (1958), "Significant trends and developments in the postwar period," in *Competitive Distribution in a Free, High-Level Economy and Its Implications for the University*, Smith A. B. ed. Pittsburgh: University of Pittsburgh Press, 1–25 pp. 17–18.
- Reilly, William J. (1931), *The Law of Retail Gravitation*, New York: William J. Reilly.
- Sethuraman, Raj, V. Srinivasan and Doyle Kim (1999), "Asymmetric and neighborhood cross-price effects: some empirical generalizations," *Marketing Science*, 18 (1), 23–41.
- Sethuraman, Raj, Gerard J. Tellis and Richard A. Briesch (2011), "How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities," *Journal of Marketing Research*, 48 (3), 457–71.
- Tellis, Gerard (1988), "The price elasticity of selective demand: a meta-analysis of econometric models of sales," *Journal of Marketing Research*, 25, 331–41.

Wagner Kamakura

Jones Graduate School of Management, Rice University,
Houston, TX 77252, United States

Praveen K. Kopalle*

Tuck School of Business at Dartmouth, Dartmouth College,
Hanover, NH 037555, United States

Donald R. Lehmann¹

Graduate School of Business, Columbia University, 507 Uris
Hall, New York, NY 10027, United States

* Corresponding author. Tel.: +1 603 646 3612;
fax: +1 603 646 1308.

E-mail addresses: kamakura@rice.edu (W. Kamakura),
kopalle@dartmouth.edu (P.K. Kopalle), drl2@columbia.edu
(D.R. Lehmann)

¹ Tel.: +1 212 854 3465; fax: +1 212 864 4857.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.