Rajkumar Venkatesan • Paul Farris • Ronald T. Wilcox

CUTTING-EDGE MARKETING ANALYTICS

Real World Cases and Data Sets for Hands On Learning

Praise for
Cutting-Edge Marketing Analytics

"*Cutting-Edge Marketing Analytics* presents managers with an excellent roadmap for marketing resource allocation. Based on my experience advising firms, I believe that the material presented in the book strikes the right balance of rigorous analysis and strategic relevance. Case studies presented in the book provide the necessary context for the application of statistical tools and allow managers and MBA students to learn the challenges in implementing analytics."

—**V. Kumar**, Executive Director, Center for Excellence in Brand and Customer Management, and Director of the Ph.D. Program in Marketing, J. Mack Robinson College of Business, Georgia State University

"This is exactly the book I have been looking for to teach customer analytics! It will fill an important gap in the market as it teaches practical approaches to gain customer insights based on big data that is increasingly available to organizations."

—**Harald J. van Heerde**, MSc, Ph.D., Research Professor of Marketing, Massey University, School of Communication, Journalism, and Marketing

"Retail's transformation is still in the early innings. The Internet and mobile have combined to create unprecedented insight into consumer behavior and customer preferences unbound by time or space. Mastery of marketing and customer analytics has become 'table stakes' for understanding and pleasing the customer—job one in retail. Practitioners looking for real world applications with a balanced overview of the underlying theory would be well served by reading this book."

—**Matt Kaness**, Chief Strategy Officer, Urban Outfitters

"I strongly recommend *Cutting-Edge Marketing Analytics* for managers seeking to build an analytics-driven marketing function. In this book, the authors have struck the right balance of analytical sophistication and managerial relevance. The case studies provide a good opportunity for applying the analytics techniques to real problems."

—**Nino Ninov**, Vice President, Strategic Research and Analysis, Rosetta Stone

Cutting-Edge Marketing Analytics

Real World Cases and Data Sets for Hands On Learning

Rajkumar Venkatesan
Bank of America Research Professor of Business Administration,
Darden Graduate School of Business Administration,
University of Virginia

Paul Farris
Landmark Communications Professor of Business Administration,
Darden Graduate School of Business Administration,
University of Virginia

Ronald T. Wilcox
Ethyl Corporation Professor of Business Administration,
Darden Graduate School of Business Administration,
University of Virginia

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Foreword

My first boss once told me, "Data is your friend," meaning that good data could help a brand manager support his or her recommendations and help get things done.

Thirty plus years later, data is more than friendly—it's cool. *Moneyball* concepts are applied beyond baseball. Nate Silver's analyses inform everything from presidential elections to weather forecasting. And powered by ever bigger data sets and the digitization of everything, nowhere is analytics more important than in marketing. For almost all marketers, analytics has become a strategic imperative: not whether, but what and how?

It is in this data-driven environment that we should ask: What do business school students really need to know about marketing analytics? And how should they learn it?

Years removed from the MBA classroom, I have some ideas on this topic. I've worked in global marketing companies spanning everything from FMCG to financial services to advertising analytics. To put it bluntly, I've pretty much seen it all—what's useful, what's not, and all of the various methodologies and metrics that go with them.

Professors Raj Venkatesan, Paul Farris, and Ron Wilcox's gem of a new book, *Cutting-Edge Marketing Analytics*, finds just the right balance. It covers virtually all of the most important research and analytics methods but does so with just the right amount of detail and depth. They put their years of experience in teaching, research, and consulting to good use here. They hit the right analytic topics—the ones that add real value in the real world—with enough detail to move students beyond the conceptual to the practical.

Importantly, *Cutting-Edge Marketing Analytics* aims to do several things that not enough MBA texts should. First, it explains in clear and cogent terms each of the major analytical tools that are critical to the marketer. Second, the real world case studies provide realistic business situations and opportunities for students to learn by doing. Third, the book has a strong decision focus: not just "what have we learned?" but "what should we do?" Marketing analytics is shown to be exactly what it should be: a strategic and tactically important tool in the hands of the action-oriented marketing decision maker.

Students who use this book will enter the business world with a much greater appreciation for the power of marketing analytics—not just what tools to use when, but greater insight into how these insights are used to make practical real world decisions. As my old boss would say, data will be their friend, and with *Cutting-Edge Marketing Analytics*, this friendship should translate into real world insights, decisions, and, ultimately, business success.

—**Randall Beard**, Global Head of Advertiser Solutions, Nielsen

About the Authors

Rajkumar Venkatesan

Bank of America Research Professor of Business Administration Rajkumar Venkatesan teaches "Marketing Strategy" and "Big Data in Marketing" in the MBA, Executive MBA, and Global Executive MBA programs at Darden. Venkatesan's research focuses on developing customer-centric marketing strategies that provide measurable financial results. Venkatesan's research has appeared in several journals, including the *Harvard Business Review*, *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *Journal of Retailing*, *Decision Support Systems*, *Marketing Letters*, and *Journal of Service Research*. He serves as an Area Editor of the *Journal of Marketing*. Many of his research publications have been recognized with prestigious awards, such as the Don Lehmann Award and the MSI Alden G. Clayton Award. He has been selected as one of the top 20 rising young scholars in marketing by the Marketing Science Institute and as one of the top 40 professors of business administration under 40 by *Poets and Quants* magazine.

Professor Venkatesan has consulted and taught in executive education programs on marketing analytics for global firms in the technology, retailing, media, consumer packaged goods, and pharmaceutical industries. For his work with IBM, he was recognized as one of the three finalists worldwide for the Informs Practice Prize Competition.

Before coming to Darden, Venkatesan taught database marketing, marketing research, and quantitative marketing models to graduate students at the University of Connecticut. There, he was the recipient of the MBA Teacher of the Year Award. He received his PhD in marketing from the University of Houston and his BE in computer engineering from the University of Madras.

Paul Farris

Landmark Communications Professor Paul Farris taught at the Harvard Business School before his appointment at the University of Virginia Darden School of Business Administration. He has worked in marketing management for UNILEVER, Germany, and in account management for the LINTAS advertising agency.

Farris's general research focus is in the area of marketing productivity and measurement. His work has been published in 10 books and more than 70 articles, appearing in professional journals and publications such as the *Wall Street Journal*, *Harvard Business Review*, *Journal of Marketing*, *Marketing Science*, *Management Science*, *Decision Sciences*, *Journal of Interactive Marketing*, *Journal of Advertising Research*, *Journal of Retailing*, *Journal of the Academy of Marketing Science*, and the *Sloan Management Review*. Farris has coauthored award-winning articles on retailer power, marketing strategy, and advertising testing. He has served as an academic trustee of the Marketing Science Institute and is a current or past member of the editorial boards for the *Journal of Marketing*, the *Journal of Retailing*, the *International Journal of Advertising*, *Marketing—Journal of Research and Management*, and the *Journal of Advertising Research*. His current research is on channel conflict and building coherent systems of marketing metrics. His coauthored book, *Marketing Metrics: 50+ Metrics Every Executive Should Master*, was selected by *Strategy + Business* as the 2006 Marketing Book of the Year.

Farris has consulted and taught executive education programs for many international companies. He has served on the boards of retailers, manufacturers, and software companies. Currently, he is on the board of directors of Sto Corp., a building materials company. Farris has also provided expert testimony in a number of marketing-related legal cases.

Ronald T. Wilcox

Ronald T. Wilcox, Ethyl Corporation Professor of Business Administration and Associate Dean of the MBA for Executives Program at the University of Virginia Darden School of Business Administration, teaches the required Marketing course in the MBA and Executive MBA programs as well as the elective "Pricing." He also teaches in numerous Executive Education programs.

His research, focused on the marketing of financial services and its interface with public policy, has appeared in leading marketing and finance journals such as the *Journal of Marketing Research*, *Management Science*, *Marketing Science*, and the *Journal of Business*. His research and writing have also appeared in the *Wall Street Journal*, *Washington Post*, *BusinessWeek*, *Fortune*, *Forbes*, and the *Weekly Standard.* He is a frequent contributor to *Forbes*. He is the author of the book *Whatever Happened* *to Thrift? Why Americans Don't Save and What to Do About It*, published by Yale University Press.

Wilcox joined the Darden faculty in 2001. He was formerly an assistant professor at the Carnegie Mellon Graduate School of Industrial Administration and an economist for the U.S. Securities and Exchange Commission.

Introduction

Your friend has sent you on a treasure hunt. She has given you clues about how to find the treasure, but you'll be left to draw on your own treasure-hunting skills to put the clues to good use.

Who is this friend of yours? It's your boss, the owner of the company for which you are the marketing manager. What is the treasure you seek? It's a business advantage that will allow your company to allocate its marketing dollars optimally and come out ahead of the competition. Those clues? That's data your company has gathered about the past behavior of customers. And what are your treasure-hunting skills? They are the tools you will find in this book—the techniques needed to analyze past marketing performance and discover unknowns that will allow you to predict the future.

The broad view of how this is done is the discipline of marketing analytics—the process of creating models helpful in understanding consumer behaviors. It is the systematic use of empirical data about customers, companies, their competition and collaborators, and industry context to inform strategic marketing decisions. The function of marketing analytics can range from reports on regular marketing activities—such as paid search advertising click-through rates—to allocating marketing resources to maximize future performance of a company's digital presence.

You have a lot to learn, and there's no time to waste. You've got treasure to find.

Why Marketing Analytics?

Dunia Finance LLC is a midsized financial services firm that operates in a unique financial market. Unlike similar institutions in the Western world, the Abu Dhabi–based company does not have the benefit of a reliable credit bureau to provide information on consumers' risk scores. Still, the company believes such scores are necessary to help it quantify decisions on product offerings. For example, risk scores indicate the interest rate Dunia should charge for a personal loan, as well as whether a personal loan customer is a good target for cross-selling credit cards. So instead of operating in the dark, the company has developed an internal system of tracking customer behavior and stores its data in a data warehouse. (For more information on Dunia Finance LLC, see Chapter 2, "Dunia Finance LLC.")[1]

Dunia is not the only company that places a high value on customer data these days. As technology has allowed firms to link customer behaviors more closely with the drivers behind those behaviors, an increasing number of companies are becoming comfortable using marketing analytics to gain a business advantage.

A 2013 report in *Forbes* magazine covered a survey of 211 senior marketers that showed that most large companies have had success using big data to understand customer behaviors. More than half (60%) of organizations that used big data a majority of the time reportedly exceeded their goals, whereas companies that used such data only occasionally reported significantly less success. Almost three quarters of companies that used big data a majority of the time were able to understand the effects of multichannel campaigns, and 70% of that group of companies said they were able to target their marketing efforts optimally.

Consider the effect of advertising. In the past, when television and print advertisements were the predominant form of pushing a firm's message, the relationship between the ads and customers' willingness to purchase the item advertised was not entirely clear. The firm rarely knew whether a customer bought the item because he or she had seen a television advertisement or because he or she had heard about it through some other channel. Collecting data about the success of the advertisements was indeed difficult.

With the advent of e-mail and web-based advertising, all that has changed. Firms are now able to closely connect their inputs (for example, ad placements) and outputs (for example, whether the target of the advertisement made a purchase). This produces a large amount of behavioral data. This data, in turn, allows companies to model existing customer behaviors and predict future behaviors more precisely. (It is important, however, to note that with big data comes a big problem—namely, the risk of false positives, or seeing patterns among chance events.)[2]

To avoid making mistakes with big data, business intuition is critical. Intuition allows the savvy marketing manager to select the correct inputs and outputs for a model. Analytics allows a company to take this traditional static dashboard of metrics or measurables and turn it into a predictive and dynamic entity.

Marketing analytics is not a new field. It simply allows companies to move beyond reports about what is happening in their businesses—and alerts about what needs to be done in response—to actually understand why something is happening based on regressions, experiments, testing, prediction, and optimization.[3] What is new is how skilled companies have become at using marketing analytics. The availability of granular customer data has transformed firms' marketing-spending decisions. Sophisticated econometrics combined with rich customer and marketing-mix data allow firms to bring science into a field that has traditionally relied on managers' intuition.[4]

What Is in This Book?

This book functions as a how-to guide on practical and sensible marketing analytics. It focuses on the application of analytics for strategic decision making in marketing and presents analytics as the engine that provides a forward-looking and predictive perspective for marketing dashboards. The emphasis is on connecting marketing inputs to customer behavior and then using the predictive models (developed using historic information, experiments, or heuristics) to develop forward-looking, what-if scenarios.

After reading this book, you will be able to (1) understand the importance of marketing analytics for forward-looking and systematic allocation of marketing resources; (2) know how to use analytics to develop predictive marketing dashboards for an organization; (3) understand the biases inherent to analytics that derive from secondary data, the cost-benefit trade-offs in analytics, and the balance between analysis and intuition; and (4) learn how to conduct data analysis through linear regression, logistic regression, or cluster analysis to address strategic marketing challenges.

This text places a big emphasis on practical guidance and striking the right balance between technical sophistication and managerial relevance. This is accomplished by real-life cases and real-life data connected to the cases that allow you to take a hands-on approach to the analysis. The book emphasizes all three aspects of marketing analytics: statistical analysis, experiments, and managerial intuition. The website http://dmanalytics.org provides videos on implementing the analytics techniques discussed in this book using commonly available statistical analysis software.

This book emphasizes that (1) analytics needs to support broader strategy; (2) inferences are inherently biased by available data, information, and techniques; (3) managers constantly make cost-benefit trade-offs in analytics; and (4) not every strategic question is answered by analytics—smart managers know to balance analysis and intuition.

Organization of the Book

This book is a reflection of the authors' experience of teaching graduate-level business students and executives, insights from academic research, and exposure to the practical aspects of marketing analytics through consulting engagements. The topics covered in this book represent the authors' impressions of the analytics techniques that are widely used in practice. This book is not intended to be an exhaustive review of marketing analytics techniques, but instead is intended to provide you exposure to how marketing analytics relates to strategic business issues.

Resource allocation provides a strategic and unifying framework for the wide-ranging purposes of marketing analytics within an organization; we therefore build marketing analytics around the resource-allocation framework. You can view analytics as the engine that provides a forward-looking perspective for marketing dashboards. The chapters in this book are organized around primary marketing functions. Section II, "Product Analytics," starts with analytics that relate to product management decisions, such as market segmentation and pricing. Section III, "Marketing-Mix Analytics," then moves to media or marketing-mix management decisions where the focus is on obtaining reliable estimates for price and advertising elasticity. Customer lifetime value is then presented as an organizing framework for customer analytics in Section IV, "Customer Analytics." Here you learn about tools to predict customer retention and profits. The emerging and popular field of analytics related to digital marketing is the focus of Section V, "Digital Analytics." It introduces design of experiments, search engine marketing, and mobile marketing. The book concludes by revisiting resource allocation and ties the different analytics tools with a case study that deals with allocating marketing resources for cross-selling products. Section VI, "Resource Allocation Revisited," then presents a forward-looking perspective on marketing analytics and provides an action plan for implementing marketing analytics in organizations and developing a learning organization that systematically includes insights gained from analytics in their strategic decisions.

Endnotes

1. Gerry Yemen, Rajkumar Venkatesan, and Samuel E. Bodily, "Dunia Finance LLC (A)," UVA-M-0842 (Charlottesville, VA: Darden Business Publishing, 2012).

2. Wes Nichols, "Advertising Analytics 2.0," *Harvard Business Review* (March 2013).

3. Thomas Davenport, *Competing on Analytics: The New Science of Winning* (Boston, MA: Harvard Business School Press, 2007).

4. Nichols.

1

A Resource-Allocation Perspective for Marketing Analytics

Introduction

Dunia Finance LLC, the midsize financial services firm in the United Arab Emirates (UAE), gains most of its customers through door-to-door sales. This makes the cost of obtaining new customers high. So the company needed to look at new ways of allocating its resources to improve its results. It decided to focus on cross-selling to existing customers to increase their customer lifetime value (CLV).

It was up to Dunia to apply a resource-allocation framework to pinpoint the best groups of customers for cross-selling. Any customer who had opted out of promotional offers was excluded. Customers close to reaching their credit card limit would be targeted for a loan. For those who had personal loans, Dunia could offer solutions based on loan type for problems the customers didn't even recognize they had.

Resource allocation is the endgame of analytics for any company. Using marketing analytics properly, any firm (not just financial services providers such as Dunia) should be able to determine the optimal level of spending it should make on each of its marketing channels to maximize success.

The Resource-Allocation Framework

Resource allocation is a four-step process. The first step is to determine the objective function. What is the metric the company wants to set as its goal for optimization? This may be one of any number of methods of assessing business success, including conversion rates to sales, incremental margins and profits, CLV, near-term sales lift, new buyers, repeat sales, market share, retention rates, cross-sell rates, future growth potential, balance sheet equity, and business valuation.

The second step is to connect the marketing inputs of a firm to the objective of resource allocation. Business managers' intuition is of paramount importance in this step, as it allows the marketer to correctly decompose a metric. For example, if a company is examining gross profits, what are the attributes of the business that contribute to those profits, and are the relationships between the various components empirical or computational (such as identity relationships)? Figure 1-1 shows one way in which gross profits might be broken down. Sales is a function of price, advertising, sales force, and trade promotions. Because gross profits minus marketing yields net profits, manipulating marketing channels can improve sales, but the different channels are also cost centers.

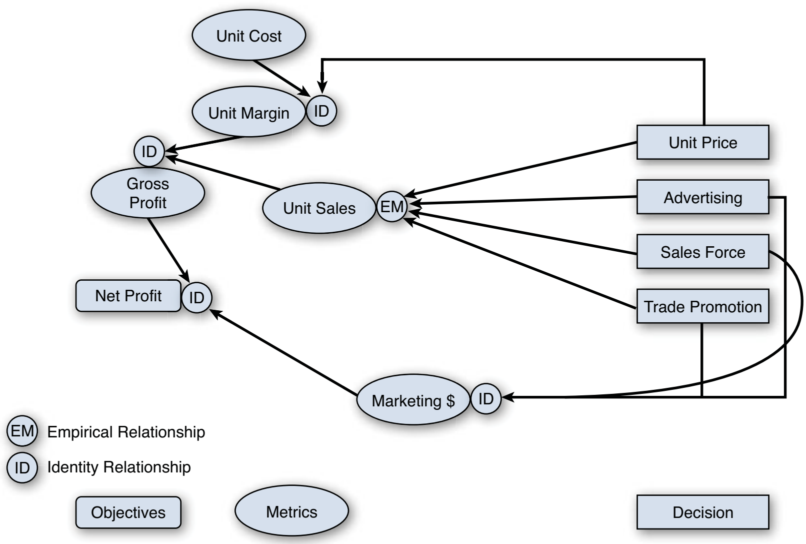

Figure 1-1 A system-of-metrics framework for net profits

Source: Created by case writer and adapted from *Marketing Metrics*.[1]

Once the marketing inputs are mapped to the objective, as shown in Figure 1-1, the marketing manager must determine the relationships that are accounting identities versus those that are empirical. An accounting identity can be computed without any unknowns. For example, in Figure 1-1, net profit is gross profit minus marketing costs. If both gross profit and marketing costs are known, net profit can be computed easily. On the other hand, the relationship between marketing costs and unit sales is more complex and driven by numerous unknowns. You cannot directly sum the investments in marketing (for example, price, advertising, sales force, and trade promotion) to obtain sales. The relationship is termed *empirical* because the manager must analyze historical data to develop a function that transforms the marketing inputs into sales (for example, a function that describes the relationship between price and sales). The transformation function ideally develops a weight that translates a product's price into sales. These weights do not provide a perfect transformation, but rather a best guess based on historical data, wherein several factors in addition to price also affect sales. This is the main difference between an identity relationship and an empirical relationship: Empirical implies a best guess or prediction; identities are certain.

The third step in the resource-allocation process is to estimate the best weights for the empirical relationships identified in the second step. A common method for identifying these weights is to build an econometric (regression) model. Which marketing inputs of interest (for example, price, advertising, sales calls) should be considered as having an effect on the dependent variable? Once this regression model is obtained, the marketing manager can predict the precise shape of the objective function. This is the mathematical model that describes the relationship between the independent variables (for example, price, advertising, sales calls) and the dependent variable (for example, market share, profits, CLV).

In the last step of the resource-allocation process, a firm can reverse the process to identify the optimal value of the marketing inputs to maximize the objective function. This gives a detailed picture of what the company's precise marketing spend should be on each channel it uses to market its product.

An Illustration of the Resource-Allocation Framework

Consider a pharmaceutical company in which the marketing department wants to determine the effects of sales calls on the profits it makes per customer (in this example, physicians are customers). In Figure 1-2, profits are broken down into number of new prescriptions and probability of new prescriptions. Both can be represented using a linear or logistic regression as a function of sales calls.

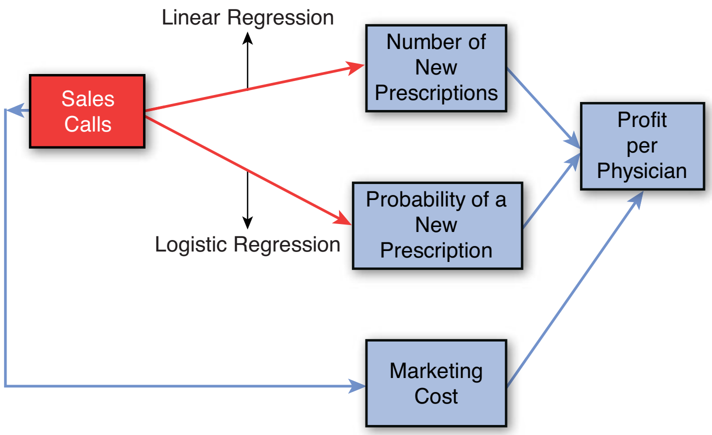

Figure 1-2 An example of the system of metrics in the pharmaceutical industry

Source: Created by case writer.

Because sales calls also represent a marketing cost, the goal is to balance their effect on the top and bottom lines to maximize profits. The marketing manager can express the relationship between sales calls and profits mathematically and perform both linear and logistic regressions[2] as follows (Equation 1):

Profit per Physician = New Prescriptions × prob (New Prescriptions) × Gross Margin% – # of Sales Calls × Unit Cost of Sales Calls

# of New Prescriptions = $a + b1 \times ln$(# of Sales Calls)

prob (New Prescriptions) = exp(u) ÷ [1 + exp(u)], where $u = c + d1 \times ln$ (# of Sales Calls) (1)

Performing the regression analyses will determine the value of a, $b1$, c, and $d1$, giving the marketing manager a mathematical way to value sales calls with respect to their ability to increase the number of prescriptions written by physicians and the probability of a new prescription. And because sales calls are a cost center, the pharmaceutical company can maximize total profits by weighting its number of sales calls subject to optimal spending under its budget limit (see Figure 1-3).

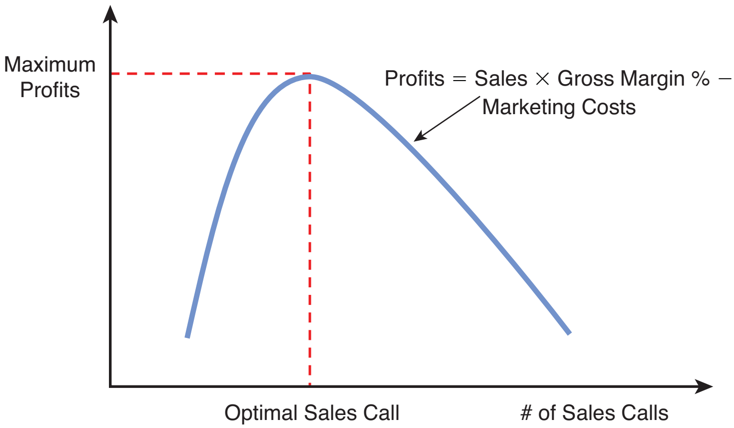

Figure 1-3 Optimal allocation of marketing spend

Source: Created by case writer.

Table 1-1 provides hypothetical data describing the effects of sales calls on profits per physician. Say the values for a, $b1$, c, and $d1$ turn out to be 0.05, 1.5, 0.006, and 1.2 based on the regression analysis.

Table 1-1 Numeric Example of Optimal Allocation of Marketing Spend

a	***b*1**	***c***	***d*1**	**Price**	**Cost of Sales Calls**
0.05	1.5	0.006	1.2	300	50

Sales Calls	**Sales**	***u***	***p*(Sales)**	**Profit**	
1	1.09	0.84	0.70	109.73	
2	1.70	1.32	0.79	181.65	Current
3	2.13	1.67	0.84	226.31	
4	2.46	1.94	0.87	252.30	
5	2.74	2.16	0.90	265.25	
6	2.97	2.34	0.91	268.74	Optimal
7	3.17	2.50	0.92	265.10	
8	3.35	2.64	0.93	255.94	
9	3.50	2.77	0.94	242.39	
10	3.65	2.88	0.95	225.27	

Source: Created by case writer.

The price of a unit (a prescription drug) is $300, and the cost of a single sales call is $50. The drug company currently calls its physicians an average of twice per month (which means that, in this example, the number of sales calls is two). Based on the estimated weights for each unknown in the described relationships, this strategy yields a profit of $181.65. If the company were to increase sales calls to six per month, the expected profits would be $268.74. Increasing sales calls beyond six per month, however, makes the cost of the sales calls higher than their incremental benefits, meaning profits start declining for sales calls of seven per month and above. In this example, six is the optimal level of sales calls because it maximizes the expected profit ($268.74) from each physician. As the example illustrates, the optimal number of sales calls that maximizes profits is critically dependent on the unknown weights of the empirical relationship.

Figure 1-4 shows a decomposition commonly used by consumer-goods companies to forecast the performance of new products. Using this model, a company can study how advertising leads to awareness and how the sales force leads to availability, among other things. Once the company understands the empirical relationships mathematically, it can calculate expected sales using simple arithmetic.

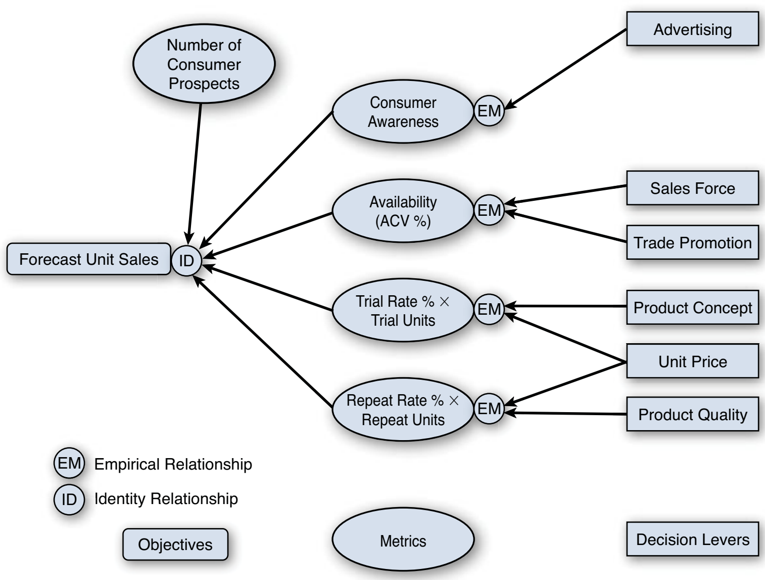

Figure 1-4 System of metrics to forecast new product sales

Source: Created by case writer adapted from Farris, Pfeifer, Bendle, and Reibstein.

Marketing analytics relies on three pillars: econometrics, experimentation, and decision calculus (Figure 1-5).

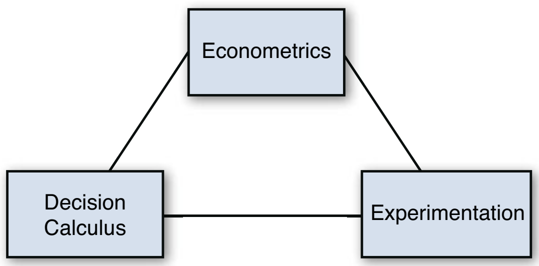

Figure 1-5 Three pillars of marketing resource allocation

Source: Created by case writer.

Managers can use econometrics when they need to make hypotheses about their business and test them by using experiments. Where the decision calculus comes down to individual companies introducing their own intuition into the equation, marketing analytics as a whole allows firms to identify best estimates for how to weight the effects of marketing activities. Intuitively, these weights should provide the best relationship between marketing inputs and consumer response. Looking at past cases wherein a firm has tried different levels of marketing inputs and observed consumer response reveals this relationship.

In the case of Dunia, if a customer purchased a service, such as a loan or credit card, the bank would track the channel through which he or she was reached, as well as behaviors such as delinquencies, and incorporate those results into its cross-selling criteria. The results would then be used to develop new models to indicate how it should introduce future offers. According to Ali Hurbas, head of Dunia's Strategic Analytics Unit, "It is not just about quantitative techniques but also business sense."[3]

Measuring ROI: Did the Resource Allocation Work?

The goal of marketing analytics is to determine the effectiveness of a company's various marketing strategies (such as its marketing mix). For each strategy, the company is looking to assess its return on investment (ROI).

Financial ROI is equal to profit over investment value. This is a yearly rate that is comparable to rate of return. Marketing ROI, on the other hand, is equal to profits related to marketing measures divided by the value of the marketing investment—which is actually money risked, not invested (Equation 2):

$$\text{Marketing ROI} = [\text{Incremental Sales} \times \text{Gross Margin} - \text{Marketing Investment}] \div \text{Marketing Investment} \tag{2}$$

Determining ROI is simple arithmetic; however, estimating and defining the effects of ROI is difficult. Imagine that Powerful Powertools spends $2 million on search engine marketing in 2012 and generates $10 million in incremental sales that year with marketing contribution margins of 50%. The company would determine its marketing ROI as follows (Equation 3):

$$\text{ROI} = (\$10\text{M} \times 0.5 - \$2\text{M}) \div \$2\text{M} = 1.5 \tag{3}$$

A marketing manager or chief financial officer (CFO) would have therefore determined that his or her return is 150% on the marketing investment. But the manager will likely still have questions. Will the investment in 2012 also pay dividends in 2013 (for example, should some new customer acquisitions in 2013 be attributed to the investment in 2012)? How was incremental gross margin determined? What is the baseline without the search engine marketing? Will doubling the investment to $4 million double the returns to $20 million in incremental sales, or are there diminishing returns to marketing? What are the longer-term effects, and what is the CLV of the customers acquired through this campaign? The goal of analytics is to accommodate these nuances of marketing's influence on sales so that the estimate of incremental sales is an accurate reflection of reality.

One major decision regarding marketing ROI concerns the choice of average versus marginal ROI. Average ROI represents the returns for any given level of marketing investment. If an executive is interested in how total returns to marketing spending have changed over the previous two years, average ROI is the right measure. Marginal ROI, on the other hand, is the return for an additional dollar spent on marketing relative to existing investment levels. The choice between marginal and average ROI relies to a large extent on whether a marketing measure may yield diminishing returns. For linear models, average and incremental returns are the same because regardless of the current level of spending, the returns will be identical (Figure 1-6). As shown in Figure 1-7, however, the current level of investment matters when calculating incremental returns in the presence of diminishing returns.

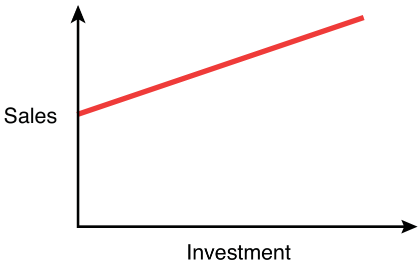

Figure 1-6 A linear sales response curve

Source: Created by case writer.

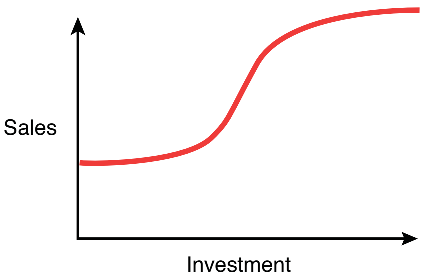

Figure 1-7 Sales response curve with diminishing returns

Source: Created by case writer.

Working with Econometrics: IBM and Others

To improve marketing success, companies must consistently make good decisions about which customers to select for targeting, the level of resources to be allocated to the selected customers, and nurturing the selected customers to increase future profitability. One example of a company that has successfully used CLV as an indicator of customer profitability and allocated marketing resources accordingly is IBM. In 2005, the computer and technology company used CLV as a criterion for determining the level of marketing contacts through direct mail, telesales, e-mail, and catalogs. An overview of the CLV management framework is shown in Table 1-2.

Table 1-2 Customer Lifetime Value Management Framework

Process	Purpose
Measure CLV	Obtain a measure of the potential value of IBM customers
Identify the drivers of CLV	Allow managers to influence CLV
Determine optimal level of contacts for each customer that would maximize his or her respective CLV	Guide managers about the level of investment required for each customer
Develop propensity models to predict which product(s) a customer is likely to purchase	Develop a product message when contacting a customer
Reallocate marketing contacts from low-CLV customers to high-CLV customers	Maximize marketing productivity

Source: Created by case writer and adapted from Kumar et al (2005).[4]

In a pilot study implemented for approximately 35,000 customers, this approach led to reallocation of resources for about 14% of the customers as compared with allocation based on past spending history, the metric IBM had previously used to target customers and allocate resources (see Figure 1-8). The CLV-based resource reallocation led to a tenfold increase in revenue (amounting to about $20 million) without any changes in the level of marketing investment.

Figure 1-8 Benefits from CLV-based resource allocation

Source: Created by case writer.

Conclusion

Managers must understand their marketing efforts as precisely as possible to determine how much to spend on each marketing channel. If paid search advertising is the most effective way of getting a firm's message in front of the right customer, why would the company spend more on print advertising? If sales calls are profitable only up to a point, the marketing manager must know at which point the calls start costing his or her company money instead of making it.

The only way to measure the effects of marketing efforts on profitability is through the best-guess relationships revealed through marketing analytics. By using statistical analysis techniques, firms can use past customer behaviors to predict how customers will react to different marketing channels; managers can then optimize spending on each channel.

Endnotes

1. Paul Farris, Phillip Pfeifer, Neil Bendle, and David Reibstein, *Marketing Metrics: The Definitive Guide for Measuring Marketing Performance* (Upper Saddle River, NJ: FT Press, 2010).

2. See Shea Gibbs and Rajkumar Venkatesan, "Multiple Regression in Marketing-Mix Models," UVA-M-0855 (Charlottesville, VA: Darden Business Publishing, 2013) for a discussion of linear regressions; see Shea Gibbs and Rajkumar Venkatesan, "Logistic Regression," UVA-M-0859 (Charlottesville, VA: Darden Business Publishing, 2013) for more on logistic regression analyses.

3. Gerry Yemen, Rajkumar Venkatesan, and Samuel E. Bodily, "Dunia Finance LLC (A)," UVA-M-0842 (Charlottesville, VA: Darden Business Publishing, 2012).

4. V. Kumar, Rajkumar Venkatesan, Tim Bohling, and Dennis Beckmen, "The Power of CLV: Managing Customer Lifetime Value at IBM," *Marketing Science*, 27, no. 4 (2008): 585–599.