Cutting-Edge Marketing Analytics: Cases and Technical Notes Bundle

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A Resource-Allocation Perspective for Marketing Analytics

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 note—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?

Companies are placing high value on customer data these days. As technology has allowed firms to link customer behaviors more closely with the drivers behind those behaviors, more and more 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 ads and customers' willingness to purchase the item advertised was not entirely clear. The firm rarely knew whether customers bought the item

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because they had seen a television advertisement or because they had heard about it through some other channel. Collecting data about the success of the advertisements was indeed difficult.

With the advent of email and web-based advertising, all that has changed. Firms are now able to closely connect their inputs (e.g., ad placements) and outputs (e.g., whether the target of the advertisement made a purchase). This produces a large amount of behavioral data. These data, in turn, allow 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.[1])

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.[2] 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.[3]

The Resource-Allocation Framework

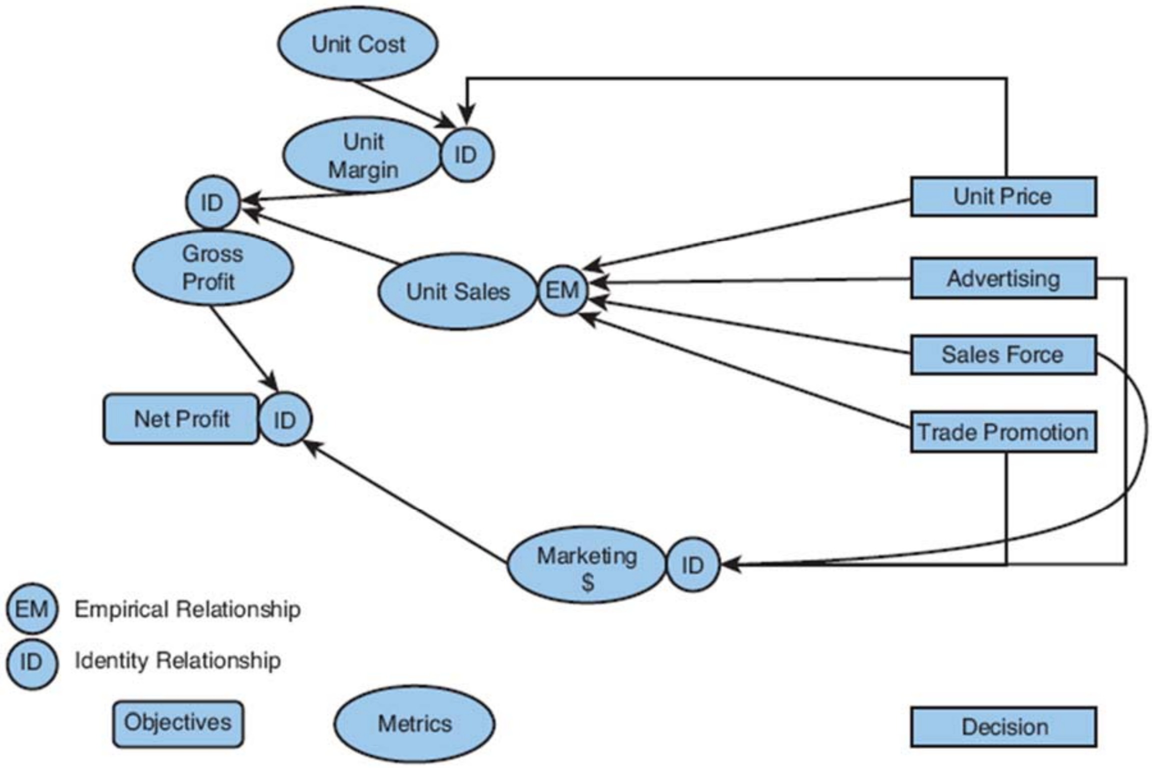
Resource allocation is the endgame of analytics for any company. Using marketing analytics properly, any firm should be able to determine the optimal level of spending it should make on each of its marketing channels to maximize success.

Resource allocation is a four-step process, the first of which 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, customer lifetime value (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 stage, 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 (i.e., identity relationships)? **Figure 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.

[1] Wes Nichols, "Advertising Analytics 2.0," *Harvard Business Review*, March 2013.
[2] Thomas Davenport, *Competing on Analytics: The New Science of Winning* (Boston, MA: Harvard Business School Press, 2007).
[3] Nichols.

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



Source: Adapted from Farris, Pfeifer, Bendle, and Reibstein.[4]

Once the marketing inputs are mapped to the objective, as shown in **Figure 1**, the marketing manager must determine which relationships are accounting identities and which are empirical. An accounting identity can be computed without any unknowns. For example, in **Figure 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 (e.g., 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 (e.g., 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

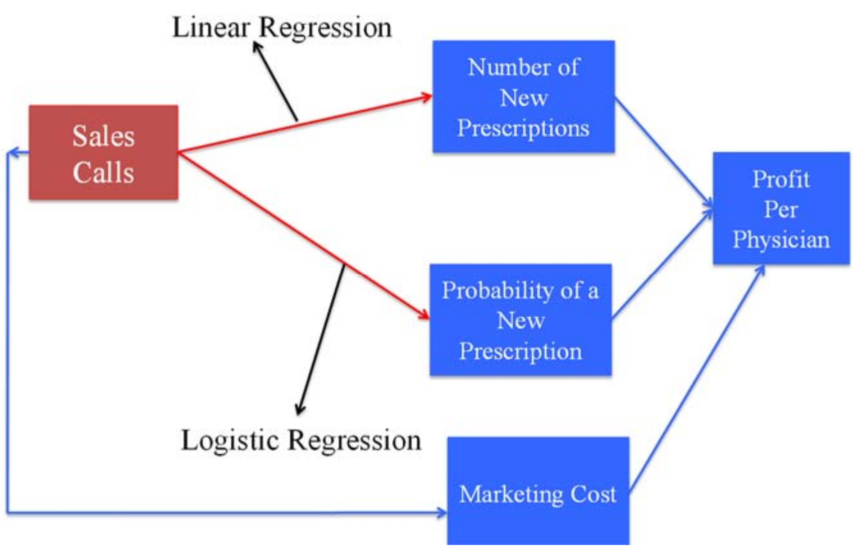
[4] Paul Farris, Phillip Pfeifer, Neil Bendle, and David Reibstein, *Marketing Metrics: The Definitive Guide for Measuring Marketing Performance* (Upper Saddle River, NJ: FT Press, 2010).

econometric (regression) model. Which marketing inputs of interest (e.g., 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 (e.g., price, advertising, and sales calls) and the dependent variable (e.g., 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.

Consider a pharmaceutical company in which the marketing department wants to determine the effects of sales calls on the profits it makes per customer (i.e., physicians are customers). In **Figure 2**, profits are broken down into number of new prescriptions and probability of new prescriptions. Both can be represented as a function of sales calls.

Figure 2. An example of the system of metrics in the pharmaceutical industry.



Source: Unless otherwise noted, all figures created by authors.

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[5] as follows (**Equation 1**):

$$\text{Profit per physician} = \text{new prescriptions} \times \text{prob (new prescriptions)} \times \text{gross margin\%} - \text{\# of sales calls} \times \text{unit cost of sales calls}$$

$$\text{\# of new prescriptions} = a + b1 \times ln(\text{\# of sales calls})$$

$$\text{prob (new prescriptions)} = \exp(u) \div [1 + \exp(u)], \text{ where } u = c + d1 \times ln(\text{\# of sales calls}). \quad (1)$$

[5] 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; and Shea Gibbs and Rajkumar Venkatesan, "Logistic Regression," UVA-M-0859 (Charlottesville, VA: Darden Business Publishing, 2013) for more on logstic regression analyses.

Performing the regression analyses will determine the values of *a*, *b*1, *c*, and *d*1, giving the marketing manager a mathematical way to value sales calls with respect to the company's 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 (**Figure 3**).

Figure 3. Optimal allocation of marketing spend.

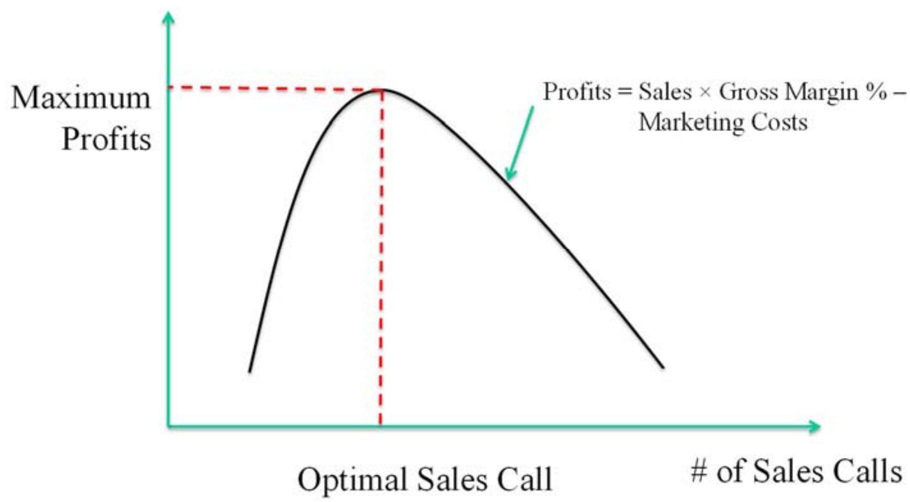


Figure 4 provides hypothetical data describing the effects of sales calls on profits per physician. Say the values for *a*, *b*1, *c*, and *d*1 turn out to be 0.05, 1.5, 0.006, and 1.2 based on our regression analysis.

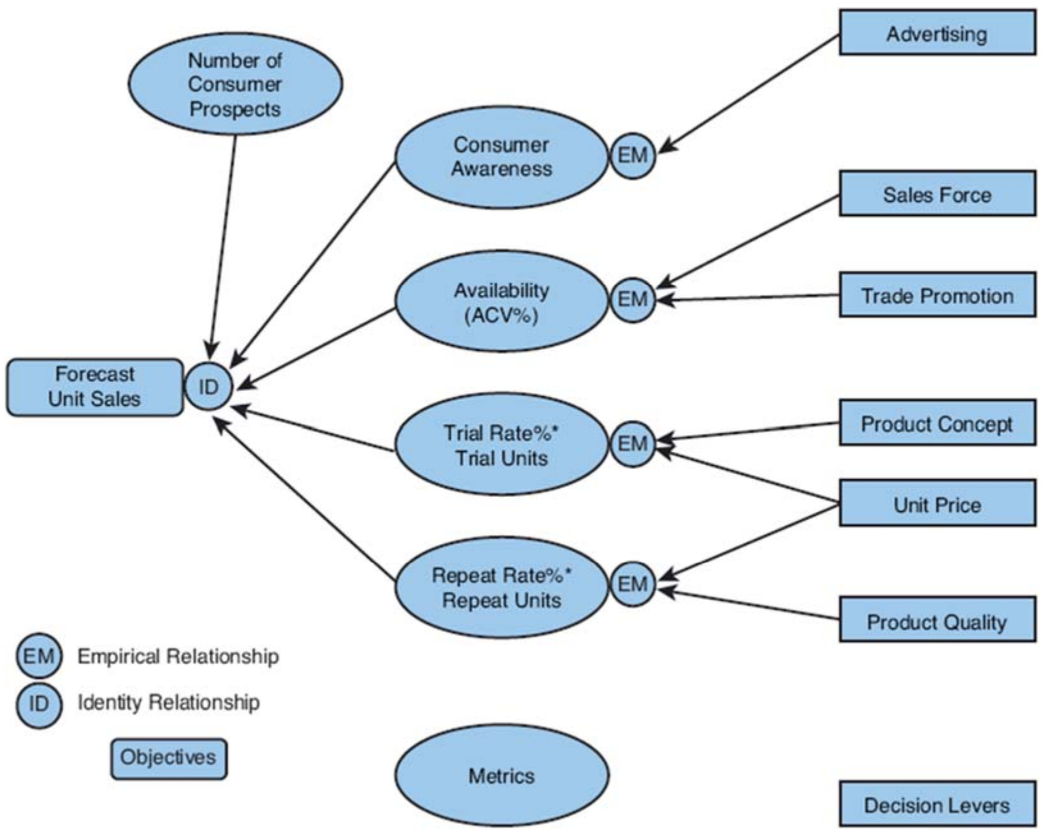
Figure 4. Numeric example of optimal allocation of marketing spend.

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	

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 5 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.

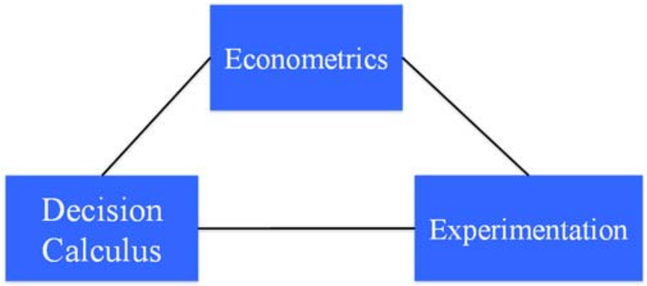
Figure 5. System of metrics to forecast new product sales.



Source: Adapted from Farris, Pfeifer, Bendle, and Reibstein.

Marketing analytics relies on three pillars: econometrics, experimentation, and decision calculus (**Figure 6**).

Figure 6. Three pillars of marketing resource allocation.



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.

Measuring ROI: Did the Resource Allocation Work?

The goal of marketing analytics is to determine the effectiveness of a company's various marketing strategies (i.e., 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**):

$$\text{Marketing ROI} = \text{Incremental Sales} \times \text{Gross Margin} - \text{Marketing Investment} \div \text{Marketing Investment}. \quad (2)$$

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**):

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

A marketing manager or CFO would have therefore determined that the 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 (i.e., 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 7**). As shown in **Figure 8**, however, the current level of investment matters when calculating incremental returns in the presence of diminishing returns.

Figure 7. A linear sales response curve.

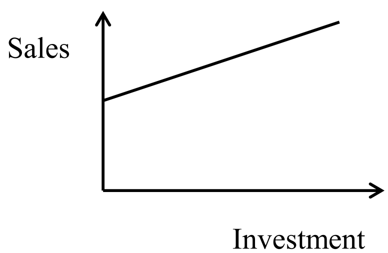
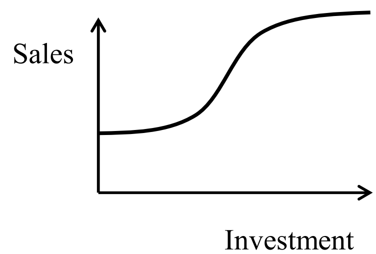


Figure 8. Sales response curve with diminishing returns.



Working with Econometrics: IBM and Others

To improve marketing success, companies must consistently make good decisions about which customers to select for targeting, what level of resources to allocate to the selected customers, and how to nurture 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, email, and catalogs. An overview of the CLV management framework is shown in **Table 1**.

Table 1. Customer lifetime value management framework.

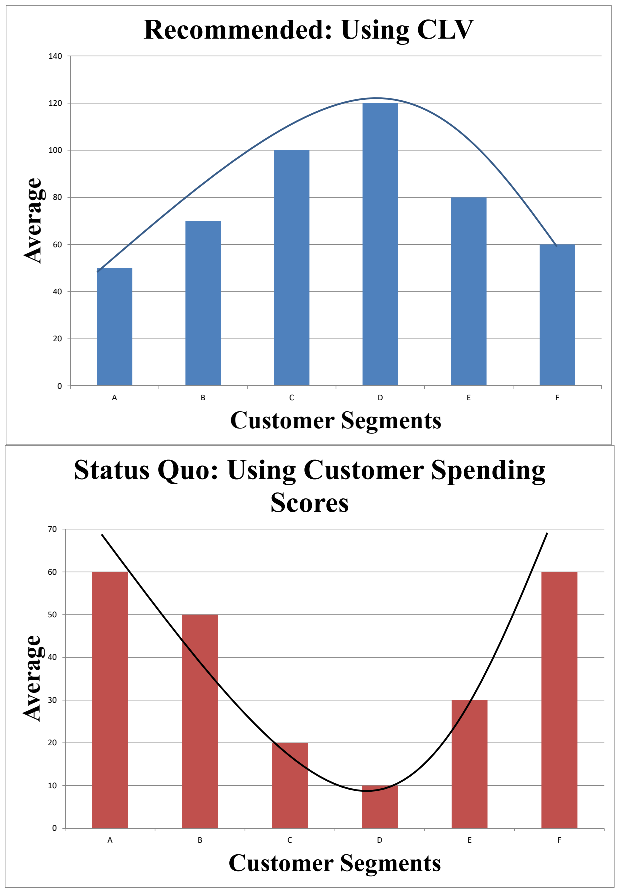
Process	Purpose
Measure CLV	To obtain a measure of the potential value of IBM customers
Identify the drivers of CLV	Allow managers to influence CLV
Determine optimal level of contacts for each customer that would maximize his or her respective CLV	To guide managers about the level of investment required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

Source: Adapted from Kumar et al. (2005)[6]

[6] 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): 585–99.

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 (**Figure 9**). 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 9. Benefits from CLV-based resource allocation.



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 the 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.

Cluster Analysis for Segmentation

Introduction

We all understand that consumers are not all alike. This provides a challenge for the development and marketing of profitable products and services. Not every offering will be right for every customer, nor will every customer be equally responsive to your marketing efforts. Segmentation is a way of organizing customers into groups with similar traits, product preferences, or expectations. Once segments are identified, marketing messages and in many cases even products can be customized for each segment. The better the segment(s) chosen for targeting by a particular organization, the more successful the organization is assumed to be in the marketplace. Since its introduction in the late 1950s, market segmentation has become a central concept of marketing practice.

Segments are constructed on the basis of customers' (1) demographic characteristics, (2) psychographics, (3) desired benefits from products/services, and (4) past-purchase and product-use behaviors. These days, most firms possess rich information about customers' actual purchase behavior, geodemographic, and psychographic characteristics. In cases where firms do not have access to detailed information about each customer, information from surveys of a representative sample of the customers can be used as the basis for segmentation.

An Example

Consider Geico, an auto insurance company. Suppose Geico hypothetically plans to customize its auto insurance offerings and needs to understand what its customers view as important from their insurance provider. Geico can ask its customers to rate how important the following two attributes are to them when considering the type of auto insurance they would use:

- savings on premium
- existence of a neighborhood agent

The importance of the attributes is measured using a seven-point Likert-type scale, where a rating of one represents *not important* and seven represents *very important*. Unless every respondent who is surveyed gives identical ratings, the data will contain variations that you can use to *cluster* or group respondents together, and such clusters *are* the segments. The groupings of customers are most similar to each other if they are part of the same segment and most different from each other if they are part of different segments. By inference,

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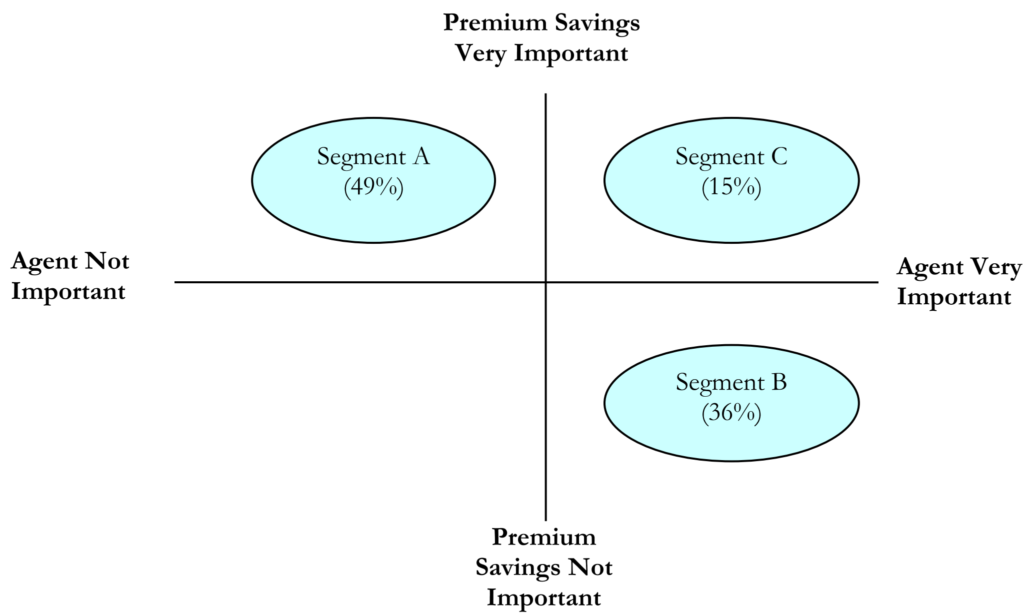
then, actions taken toward customers in the same segment should lead to similar responses, and actions taken toward customers in different segments should lead to different responses.

Another way of saying this is that the aspects of auto insurance that are important to any given customer in one segment will also be important to other customers in that same segment. Furthermore, those aspects that are important to that customer will be different from what is important to a customer in a different segment. **Figure 1** shows what the analysis in this example might look like:

Figure 1. Segmentation of Geico customers.



Source: All figures created by case writer, unless otherwise noted.

The analysis shows three distinct segments. The majority of Geico's customers (Segment A, 49%) prefer savings on their premium, and they do not prefer having a neighborhood agent. Customers who belong to Segment B (about 36%) prefer having a neighborhood agent and premium savings is not important to them. Some customers (Segment C, 15%) prefer both the savings on their premium as well as a neighborhood agent. This analysis shows that Geico can benefit by adding an offline channel (i.e., developing a network of neighborhood agents) to serve Segment B and also charge a higher premium to them for providing this convenience. Of course, the caveat is the increased competition with other insurance providers, such as Allstate and State Farm, who already provide this service.

Cluster Analysis

Cluster analysis is a class of statistical techniques that can be applied to data that exhibit natural groupings. Cluster analysis makes no distinction between dependent and independent variables. The entire set of interdependent relationships is examined. Cluster analysis sorts through the raw data on customers and groups them into clusters. A *cluster* is a group of relatively homogeneous customers. Customers who belong to the same cluster are similar to each other. They are also dissimilar to customers outside the cluster, particularly customers in other clusters. The primary input for cluster analysis is a measure of similarity between customers, such as correlation coefficients, distance measures, and association coefficients.

The following are the basic steps involved in cluster analysis:

1. Formulate the problem—select the variables you want to use as the basis for clustering.
2. Compute the distance between customers along the selected variables.
3. Apply the clustering procedure to the distance measures.
4. Decide on the number of clusters.
5. Map and interpret clusters—draw conclusions—illustrative techniques like perceptual maps are useful.

Distance Measures

The main input into any cluster analysis procedure is a measure of distance between individuals who are being clustered. The objective of a distance measure is to quantify the difference between two individuals on the variables you are using for the segmentation. A shorter (longer) distance between two individuals would imply they have similar (dissimilar) preferences on the segmentation variables. Distance between two individuals is obtained through a measure called *Euclidean distance*. If two individuals, Joe and Sam, are being clustered on the basis of *n* variables, then the Euclidean distance between Joe and Sam is represented as:

$$\text{Euclidean distance} = \sqrt{\left(x_{Joe,1} - x_{Sam,1}\right)^2 + \ldots + \left(x_{Joe,n} - x_{Sam,n}\right)^2}$$

where:

$x_{\text{Joe},1}$ = the value of Joe along variable *1*, and

$X_{\text{Sam},1}$ = the value of Sam along variable *1*.

A pairwise distance matrix among individuals who are being clustered can be created using the Euclidean distance measure. Extending the preceding example, consider three individuals—Joe, Sam, and Sara—who are being clustered based on their preference for Premium Savings and a Neighborhood Agent. The importance ratings on these two attributes for Joe, Sam, and Sara are shown in Table 1.

Table 1. Sample data for cluster analysis.

Individual Name	**Importance Score**	
	Premium Savings	Neighborhood Agent
Joe	4	7
Sam	3	4
Sara	5	3

The Euclidean distance between Joe and Sam is obtained as:

$$\text{Euclidean distance (Joe, Sam)} = \sqrt{(4-3)^2 + (7-4)^2} = 3.2.$$

The first term in this Euclidean distance measure is the squared difference between Joe and Sam on the importance score for Premium Savings, and the second term is the squared difference between them on the importance score for Neighborhood Agent. The Euclidean distances are then computed for each pairwise combination of the three individuals being clustered to obtain a pairwise distance matrix. The pairwise distance matrix for Joe, Sam, and Sara is shown in **Table 2**.

Table 2. Pairwise distance matrix.

	Joe	Sam	Sara
Joe	0	3.2	4.1
Sam		0	2.2
Sara			0

The distance between Joe and Sam is 3.2, as shown in **Table 2**. This pairwise distance matrix is then provided as an input to a clustering algorithm.

K-Means Clustering Algorithm

K-means clustering belongs to the nonhierarchical class of clustering algorithms. It is one of the more popular algorithms used for clustering in practice because of its simplicity and speed. It is considered to be more robust to different types of variables, is more appropriate for large datasets that are common in marketing, and is less sensitive to some customers who are outliers (in other words, extremely different from others).

For K-means clustering, the user has to specify the number of clusters required before the clustering algorithm is started. The basic algorithm for K-means clustering is as follows:

Algorithm

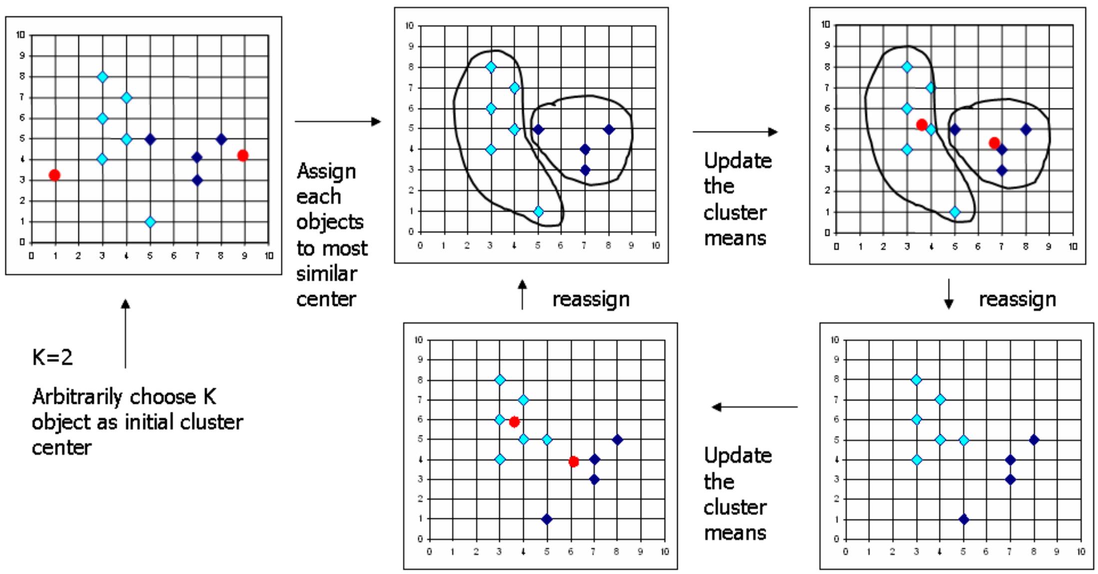
1. Choose the number of clusters, k.
2. Generate k random points as cluster centroids.
3. Assign each point to the nearest cluster centroid.
4. Recompute the new cluster centroid.
5. Repeat the two previous steps until some convergence criterion is met. Usually the convergence criterion is that the assignment of customers to clusters has not changed over multiple iterations.

A cluster centroid is simply the average of all the points in that cluster. Its coordinates are the arithmetic mean for each dimension separately over all the points in the cluster. Consider Joe, Sam, and Sara in the previous example. Let's represent them based on their importance ratings on Premium Savings and Neighborhood Agent as: Joe = {4,7}, Sam = {3,4}, Sara = {5,3}. If you assume that they belong to the same cluster, then the center for their cluster is obtained as:

$$\text{Cluster centroid } Z = (z_1, z_2) = \{(4+3+5)/3,\ (7+4+3)/3\}.$$

z_1 is measured as the average of the ratings of Joe, Sam, and Sara on Premium Savings. Similarly, z_2 is measured as the average of their ratings on Neighborhood Agent. **Figure 2** provides a visual representation of K-means clustering.

Figure 2. Visual representation of K-means clustering.



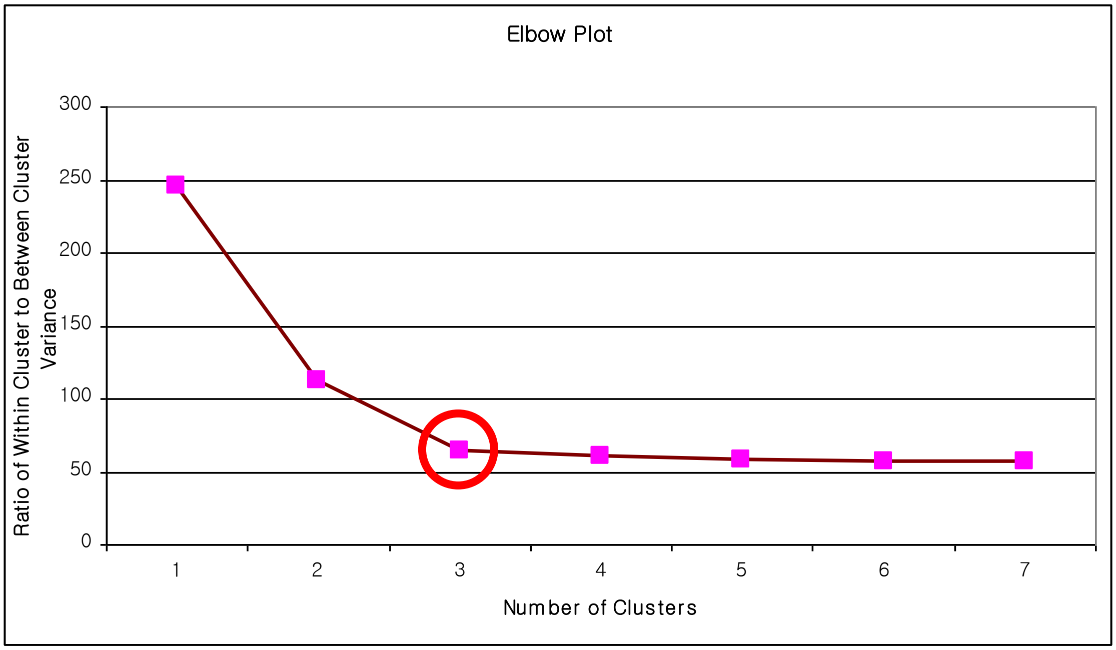
Number of clusters

One of the main issues with K-means clustering is that it does not provide an estimate of the number of clusters that exists in the data. The K-means clustering has to be repeated several times with different "Ks" (or number of clusters) to determine the number of clusters that is appropriate for the data. A commonly used method to determine the number of clusters is the elbow criterion.

The elbow criterion states that you should choose a number of clusters so that adding another cluster does not add sufficient information. The elbow is identified by plotting the ratio of the *within cluster variance* to *between cluster variance* against the number of clusters. The within cluster variance is an estimate of the average of the variance in the variables used as a basis for segmentation (Importance Score ratings for Premium Savings and Neighborhood Agent in the Geico example) among customers who belong to a particular cluster. The between cluster variance is an estimate of the variance of the segmentation basis variables between customers who belong to different segments. The objective of cluster analysis (as mentioned before) is to minimize the within cluster variance and maximize the between cluster variance. Therefore, as the number of clusters is increasing, the ratio of the within cluster variance to the between cluster variance will keep decreasing.

But at some point, the marginal gain from adding an additional cluster will drop, giving an angle in the graph (the elbow). In **Figure 3**, the elbow is indicated by the circle. The number of clusters chosen should therefore be 3.

Figure 3. Elbow plot for determining number of clusters.



It should also be noted that the initial assignment of cluster seeds has a bearing on the final model performance. Some common methods for ensuring the stability of the results obtained from K-means clustering include:

- Running the algorithm multiple times with different starting values. When using random starting points, running the algorithm multiple times will ensure a different starting point each time.
- Splitting the data randomly into two halves and running the cluster analysis separately on each half. The results are robust and stable if the number of clusters and the size of different clusters are similar in both halves.

Profiling Clusters

Once clusters are identified, the description of the clusters in terms of the variables used for clustering—or using additional data such as demographics—helps to customize marketing strategy for each segment. This process of describing the clusters is called profiling. **Figure 1** is an example of such a process. A good deal of cluster-analysis software also provides information on which cluster a customer belongs to. This information can be used to calculate the means of the profiling variables for each cluster. In the Geico example, it is useful to investigate whether the segments also differ with respect to demographic variables such as age and income. In **Table 3**, consider the distribution of age and income for Segments A, B, and C as provided in **Figure 1**.

Table 3. Age and income distribution for segments.

Segment	Mean		Range	
	Age	Income ($)	Age	Income ($)
A	21	15,000	16–25	0–25,000
B	45	120,000	33–55	75,000–215,000
C	39	40,000	39–54	24,000–60,000

Mean represents the averages of age and income of customers belonging to a particular segment. *Range* represents the minimum and maximum values of age and income for customers in a segment. Whereas the *mean* is useful for identifying the central tendency of a segment, the *range* helps in evaluating whether the segments overlap with regards to the profile variable.

From **Table 3**, you see that Segment A customers who prefer high savings on their premium and do not prefer having a neighborhood agent tend to be younger and have low income. These could probably be college students or recent graduates who are more comfortable with transacting online. Customers who belong to Segment B, on the other hand, are older and have higher income levels. It would be interesting to evaluate if these customers also tend to be married with kids. The security of having a neighborhood agent who can help in case of an accident or emergency is very important to them, and they do not mind paying a higher price for this sense of security. These customers may also not be comfortable in transacting (or providing personal information) online.

Finally, while Segment C customers are as old as Segment B customers, they tend to have lower incomes and do not prefer to have a neighborhood agent (probably because of low disposable incomes). Identification of the segments through these demographic characteristics enables a marketer to target as well as customize communications to each segment. For example, if Geico decides to develop a network of neighborhood agents, it can first focus on neighborhoods (identified through their zip codes) that match the profile of Segment B customers.

Conclusion

Given a segmentation basis, the K-means clustering algorithm would identify clusters and the customers that belong to each cluster. The management, however, has to carefully select the variables to use for segmentation. Criteria frequently used for evaluating the effectiveness of a segmentation scheme include: *identifiability*, *sustainability*, *accessibility*, and *actionability*.[1] *Identifiability* refers to the extent that managers can recognize segments in the marketplace. In the Geico example, the profiling of customers allows you to identify customer segments through their age and income information. PRIZM and ACORN are popular databases that provide geodemographic information that can be used for segmentation as well as profiling. The *sustainability* criterion is satisfied if the segments represent a large enough portion of the market to ensure profitable customization of the marketing program. The extent to which managers can reach the identified segments through their marketing campaigns is captured by the *accessibility* criterion. Finally, *actionability* refers to whether customers in the segment and the marketing mix necessary to satisfy their needs are consistent with the goals and core competencies of the firm. The success of any segmentation process therefore requires managerial intuition and careful judgment.

[1] For more details, refer to Wagner Kamakura and Michel Wedel, *Market Segmentation: Conceptual and Methodological Foundations*, 2nd ed. (Norwell, MA: Kluwer Academic Publishers, 2000).

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Segmentation at Sticks Kebob Shop

Sticks Kebob Shop, headquartered in Charlottesville, Virginia, had a problem. But it was a good problem to have.

A restaurant chain in a fast-growing segment of the food-service industry, Sticks expected to add about one restaurant to its portfolio every year or two starting in 2014. A sticking point was picking the right markets to enter and then deciding on (and waiting for) the right location.

Since opening its first quick-service restaurant (QSR) in 2001 in Charlottesville, Sticks had added another store in town (**Figure 1**), as well as one in both Richmond, Virginia, and Williamsburg, Virginia. Because Richmond was a larger city, the Sticks executive team—composed of Chris DuBois, Ty Austin, Ingmar Leliveld, and Bill Hamilton—was interested in opening a second location there. They had narrowed their search down to four specific targets, but before selecting the optimal site, the team wanted to gain a better sense of who Sticks' customers were, which location would attract the best customers, and how to best connect with customers.

The restaurant-industry veterans had a rough idea of their customer base from anecdotal evidence. An opportunity to gather survey data to confirm their hypotheses presented itself. Would the demographic and psychographic assumptions they had gathered from talking to people in stores align with the survey answers? And what would the data tell them about where to locate their next store and what marketing channels and messages would be most effective in promoting it?

Figure 1. First Sticks location in Charlottesville.

Second Sticks Location in Charlottesville.

Source: Company photographs.

The Sticks Story

While working at Hamiltons' at First & Main, a fine dining restaurant in Charlottesville, Dubois and Austin realized that they needed a good place to grab a bite to eat before going to work on the night shift. So when Bill Hamilton, who owned the restaurant with his wife, approached the pair about going into business together, they decided to pursue a concept that could deliver a good meal without much fuss. "We went out for some beers and decided we were going to do it," DuBois said. "We had not settled on a concept for the restaurant at the time."[1]

The team finally settled on kebobs after kicking around food ideas ranging from BBQ to curry. In 2001, the idea of the fast-casual restaurant—essentially the QSR segment minus traditional fast food—was still in its infancy. Chipotle had just begun to expand outside its home state of Colorado. The team's idea was to offer high-quality, healthy food in a less stuffy environment and to deliver it quickly. According to the Sticks website, they wanted to "create a safe haven for fellow foodies, busy families, and health-conscious diners." It was a niche the team thought Charlottesville lacked, and one they decided that they could satisfy effectively.

The Sticks chain learned a lot about its customer base over the years (e.g., executives had increased their focus on the healthy food angle). But Sticks also made sure that its cuisine remained accessible to a broader audience. Sticks didn't claim to offer authentic Middle Eastern food. For example, instead of using the original term *baba ganouj* for one of its menu items, Sticks called it roasted eggplant salad. (See **Exhibit 1** for a sample menu.)

Planning for Expansion

According to DuBois, Sticks' long-term expansion plan was focused on the I-64 corridor that ran across Virginia. Richmond was the primary immediate target because the brand had already been established there, and a second store would lend efficiencies in marketing, labor, and the like. Beyond that, the company planned to look in Virginia at Newport News, Hampton, Virginia Beach, Norfolk, Harrisonburg, Lynchburg, and Fredericksburg. The eventual goal was to grow from four stores to eight from 2014 to 2020, at which point the company would reassess and consider moving into the Northern Virginia and Washington, DC, areas, which would require a multiple-store launch.

In addition to adding restaurants, Sticks expected to expand in two other ways. It was in the process of launching a packaged version of its signature hummus for sale in retail outlets, and planning to purchase a food trailer to increase its off-site vending, including at an outdoor concert series in Richmond.

The Sticks growth plan had been tempered slightly in the past several years: the Richmond location was growing more slowly than the company would have liked. The restaurant had opened right on the cusp of the 2008 recession and improved sales by about 10% every year, but the baseline had been lower than expected (see **Figure 2** for Sticks location addresses as of 2014).

[1] All quotes attributed to Chris DuBois and Ty Austin are from January 2014 author interviews.

Figure 2. Sticks locations as of 2014.

Store Name	Address
Preston Avenue, Charlottesville	917 Preston Avenue Charlottesville, VA, 22903
Pantops, Charlottesville	1820 Abbey Road Charlottesville, VA, 22911
Willow Lawn, Richmond	1700 Willow Lawn Dr. Willow Lawn Plaza Richmond, VA, 23221
Courthouse Commons, Williamsburg	5223 Monticello Avenue Williamsburg, VA, 23188

Source: Created by author.

The customer survey was an opportunity to ensure that the next Richmond store was a strong fit with its market. DuBois said the goal was to gather data that could assist in identifying real estate options, improving the team's knowledge of customer demographics and psychographics, and providing insight into how customers perceived Sticks relative to other restaurants they frequented in terms of value for the money and other attributes.

DuBois and Austin described typical Sticks customers—based on knowledge gained while working as managers in the two Charlottesville stores—as people "in their 30s who have a smartphone and want food that's both healthful and satisfying." The base skewed more toward women making dining decisions for their families, but it also did well with single people ranging from their mid-20s to their mid-40s and professionals on their lunch break. More recently, Sticks identified growing interest in its Mediterranean-inspired menu from an older demographic that emphasized an active lifestyle and healthy eating.

"It may sound like a cliché, but a lot of our customers are soccer moms," DuBois said. "Soccer is a big thing in the area. We have proven to be a good fit for people who are involved in sports—either for themselves or for their kids."

The Sticks team knew that offering a quick, healthy meal option would be a big part of its appeal when it opened in 2001 but debated about how heavily to market that attribute; they did not want Sticks' cuisine to be thought of as health food, because most people at the time associated health food with unsatisfying food. The team also wanted to combat the idea that the restaurant was exotic and unfamiliar, so it would appeal to customers who generally selected more familiar options, such as Applebee's, Arby's, or Ruby Tuesday.

DuBois and Austin said they consistently heard from customers that they appreciated the variety of the Sticks menu and its filling but nutritious food, well-priced selections, and fast deliveries. Management considered other fast-casual restaurants such as Chipotle and Panera to be competitors, as the restaurant tended to attract most of its customers on weekday afternoons. The volume of visits during nights and weekends was generally lower.

"The challenge is not expecting people to behave in a way you want them to but instead letting them do more of what they already want to do themselves," Austin said. "We have to remind ourselves to work from and gradually expand people's given behaviors. We try to keep hurdles low for new customers yet offer enough options for novelty for existing customers."

The Fast-Food Industry

Fast-casual QSRs typically aimed to deliver food fast but operated outside the traditional fast-food market by offering carefully selected ingredients and healthier options overall. For Sticks, that also meant avoiding being pigeonholed as a health food restaurant and striving to become a national brand, as opposed to being known as a college-town niche store. Sticks wanted its customers to leave the restaurant feeling full and satisfied and as if they had made a smart dining choice.

From 2010 to 2012, the fast-casual industry was one of the fastest-growing segments of the restaurant business, according to *QSR* magazine, and Panera was the clear leader (**Table 1**). According to food industry analyst Technomic, Inc., several other fast-casual restaurants were among the fastest-growing QSRs in the country (**Table 2**).

Table 1. Top 10 fast-casual restaurants.

FAST-CASUAL RANK	**CHAIN**	**2012 SALES** (in millions of dollars)	**TOTAL UNITS IN 2012**	**CHANGE IN UNITS FROM 2011**
1	Panera	$3,861.0	1,652	111
2	Chipotle	$2,731.2	1,410	180
3	Jimmy John's	$1,262.8	1,560	229
4	Zaxby's	$979.3	565	25
5	Steak 'N Shake	$857.5	501	10
6	Qdoba	$583.2	627	44
7	Jason's Deli	$578.9	245	10
8	El Pollo Loco	$563.0	397	3
9	Boston Market	$559.0	469	(12)
10	Moe's	$452.0	482	43

Data source: Sam Oches, "The *QSR* 50," August 2013, *QSR*, http://www.qsrmagazine.com/reports/qsr50-2013-top-50-chart (accessed Feb. 24, 2014).

Table 2. Fastest-growing QSR chains (more than $200 million in annual sales).

RANK	**CHAIN**	**2011 US SALES** (in thousands of dollars)	**2010 US SALES** (in thousands of dollars)	**% CHANGE**	**$ CHANGE** (in thousands of dollars)
1	Five Guys	950,630	716,105	32.8	234,525
2	Chipotle	2,260,548	1,831,922	23.4	428,626
3	Jimmy John's	895,000*	735,000*	21.8	160,000
4	Firehouse Subs	284,581	235,000	21.1	49,581
5	Raising Cane's	206,301	174,608	18.2	31,693
6	Little Caesars	1,480,000*	1,253,000*	18.1	227,000
7	Noodles & Company	300,000	261,000	14.9	39,000
8	Wingstop	381,660	332,612	14.7	49,048
9	Chick-Fil-A	4,050,992	3,583,000	13.1	467,992
10	Qdoba	531,000*	475,000*	11.8	56,000

*Technomic estimate.

Data source: "Fastest Growing Limited-Service Chains > $200 Million," Technomic, Inc., 2012, https://www.technomic.com/Resources/Industry_Facts/dyn_10_limited_sales.php (accessed Feb. 24, 2014).

Sticks also fell into another fast-growing segment of restaurants: ethnic food. Although the Mexican segment was the clear ethnic food leader, DuBois said Mediterranean restaurants were also growing quickly. They were part of a group (specialty fast-casual restaurants) that made up 9% of all fast-casual restaurants (**Table 3**).

Table 3. Menu composition within the fast-casual segment.

RANK	CATEGORY	MARKET SHARE
1	Mexican	20%
2	Bakery/Café bagel	18%
3	Other sandwich	16%
4	Hamburger	11%
5	Chicken	9%
6	Specialty*	9%
7	Pizza	7%
8	Asian	6%

*Barbecue, healthy, Italian, other ethnic (including Mediterranean), and soup.

Data source: "Menu Composition Within the Fast-Casual Segment," https://www.technomic.com/Resources/Industry_Facts/dyn_Menu_Composition_within_the_fast_casual.php (accessed Jan. 6, 2014).

Sticks was somewhat unique, however, in that it marketed itself without referring to its ethnicity. The goal of the restaurant's owners was to make the food as accessible as possible and not intimidate customers. Sticks did not expect to attract the adventurous diner looking for authentic ethnic food; it tried to position itself as menu alternative alongside Panera and Chipotle, rather than local Middle Eastern restaurants.

Still, Austin and DuBois watched the growth of other Mediterranean restaurants closely. They saw a larger chain from Alabama called Zoë's Kitchen move into Charlottesville and Richmond in 2014, and Taziki's (also a growing chain from the South) operating a similar concept, also in Richmond. In addition to those, Austin said Roti out of Chicago and Garbanzo out of Denver were other Mediterranean QSR brands worth following—both chains had high-quality management and were well funded. Despite others entering Sticks' local markets, the team didn't see the competition as all bad.

"Most importantly, these larger chains help validate the concept for us," DuBois said. "They also help generate new interest in our category, which is a net benefit. But at the same time, we have to be dynamic and keep creating and emphasizing our unique points of differentiation. We are well aware of direct competition but don't want that to distract us from succeeding on our own terms."

Sticks' Existing Marketing Initiatives

Since it launched in 2001, Sticks had made a concerted effort to better understand its customer base. Over the years, the team changed its message in subtle ways in response to what it had learned by switching from Styrofoam containers to reusable plates and silverware and honing its marketing message.

Sticks had used simple, brand-recognition-focused advertising campaigns in the Charlottesville area to reinforce its existing reputation. In its other markets, it had focused on more extensive campaigns and made product samples available to introduce what it offered to new audiences. Its most extensive television campaign featured animated spots. The advertisements had not shown the restaurant's food; they were more geared toward general brand recognition, DuBois said. The spots were used extensively on the Charlottesville broadcast stations, where brand recognition was most powerful for Sticks; however, the team also used the campaign in Richmond and reported some success.

Sticks had also tried to expand its existing customer base through television. The company televised an announcement of a weekend discount on its popular chicken platter and saw a spike in traffic for what was otherwise a slower time of the week.

The team had used print advertisements primarily in the Richmond market, where it was looking to expand. In that city, the team determined that customers enjoyed reading the alternative newspaper *Style Weekly*, which proved to be an inexpensive way to reach a desired audience. Sticks regularly enlisted local marketing experts to fine-tune decisions about how to reach the Richmond audience.

Sticks had found partnerships to be particularly beneficial in Charlottesville both in a community service capacity or the restaurant's ongoing advertising campaign with the University of Virginia (UVA) sports properties. In 2013, the brand was in its second year working with UVA and expanded its campaign on the strength of the first year, which featured coupons in the men's basketball, baseball, and soccer team game programs. Austin and DuBois said they considered the coupons a success, particularly the one offered during the men's basketball team's ACC home games. Also in 2013, Sticks added several UVA women's sports to the campaign.

The impetus behind the partnership with UVA was due largely to the university's own demographic and psychographic breakdown of its audience. Authors determined that UVA's sports fans were particularly active in tennis and golf, dined in various fast-casual restaurants, enjoyed artisanal beverages, and skewed toward higher household incomes. In addition to offering the chance to stay in view of a crowd of people similar to those who Sticks believed to be its customers, the campaign also allowed it to build its brand among UVA students.

"The gravy is to attract students as well," DuBois said. "But our main focus is the family and the long-term local resident, rather than the mostly transient students. We looked at that, and it seems to match up with who we already feel are our loyal core customers, so it lets us serve them better."

DuBois and Austin also said Sticks had considered its two alternative growth strategies, retail sales and off-site vending, to be promising marketing avenues. Finally, Sticks began offering a successful mobile smartphone application that enabled advance ordering and faster pickup in the store in an effort to align it with its technologically savvy base.

Implementing the Survey

Sticks was relatively certain it had a good handle on its customer base—active people making choices for their families and working professionals looking for a quick, healthy lunch—but the team wanted to confirm that hypothesis. So management worked with an outside consultant to prepare and distribute a survey of both customers and noncustomers as follows:

- Create a small but in-depth survey of 5 to 10 existing customers to better inform suggestions for the questionnaires and desired outputs from the study.
- Prepare the customer and noncustomer surveys for distribution.
- Sample 200 existing customers, primarily from the Richmond market, using Surveymonkey.com.
- Utilize a third-party vendor to sample 200 noncustomers online.

A quick review of the survey (**Exhibit 2**) indicated that many of the hypotheses held by the Sticks executives were upheld. But several of their assumptions proved to be wrong. For the first time Sticks recognized the importance of its white-collar lunch crowd, and where it had once considered other fast-casual chains such as Panera and Chipotle to be rivals, it now saw that it could become part of customers' regular lunch rotation along with those restaurants. Could Sticks focus on building the loyalty of those customers' and making them dinner and weekend customers, as well?

The difficulty for the team was examining its value proposition and customer profile and mapping this data to a demographics-based real estate model. While the data the team had collected certainly lent insight into just who Sticks customers were, would it lead it to picking the correct location for next Sticks Richmond store? Was it even the right data needed to make the decision?

Exhibit 1

Segmentation at Sticks Kebob Shop

Sample Sticks Menu

Start Here

Sandwich
- Choice of Kebob
- Choice of Homemade Sauce
- Wrapped in Grilled Flatbread
- Fresh Lettuce and Tomato

Salad
- Choice of Kebob
- Crisp Romaine Lettuce with Cucumber, Tomato and Carrot
- Grilled Onions and Pita Croutons
- Sesame-Lemon Vinaigrette

Platter
- Choice of Kebob
- Choice of Homemade Sauce
- Choice of Homemade Side Dish
- Herbed Basmati Rice and Grilled Flatbread

Side Sampler $6.99
- Choice of 4 Homemade Sides
- Herbed Basmati Rice and Grilled Flatbread

Soup + Salad Platter $4.99
- Soup of the Day
- Half House Salad
- Grilled Flatbread

Kids' Meal $4.99
- Grilled Chicken Kebob
- Choice of Rice or Fries
- Carrot Sticks
- Small Drink, Juice or Milk

Pick-A-Stick

	sandwich	salad	platter
Chicken Breast with Fresh Herbs	$6.49	$7.25	$7.99
Chili-Spiked Beef Sirloin*	$6.49	$7.25	$7.99
Lemon-Garlic Shrimp	$7.49	$8.25	$8.99
Rosemary-Rubbed Leg of Lamb*	$8.49	$9.25	$9.99
Pork Loin with African Spices	$6.49	$7.25	$7.99
Sticks Housemade Kibbeh	$6.49	$7.25	$7.99
Mixed Garden Vegetables with Basil Oil	$5.99	$6.75	$7.49
Falafel	$5.99	$6.75	$7.49

*Consuming raw or undercooked meats may increase your risk of foodborne illness.

Double Down $3.50
Add any skewer to a sandwich, salad or platter!
Add a lamb skewer $4.50

Add-Ons $.75
- Choose Feta Cheese, or Cured Olives or Grilled Onion
- 2 oz of any Side Dish

Homemade Sauces
Cucumber-Yogurt, Fire-Roasted Red Pepper, Sesame-Lemon Vinaigrette, Creamy Cilantro-Lime

Pick-A-Side

	small	large
Hummus *Delicious purée of chick peas, olive oil, lemon,garlic and sesame*	$1.99	$3.69
Roasted Eggplant Salad *Made with onions, lemon and fresh mint*	$1.99	$3.69
Sesame Beans *Green beans with toasted sesame seeds, lemon, garlic and spices*	$1.99	$3.69
Cucumber, Tomato & Red Onion Salad *With olive oil, red wine vinegar and oregano*	$1.79	$3.49
Marinated Grilled Veggies *Squashes, peppers, onions, and eggplant grilled with olive oil and fresh basil*	$1.79	$3.49
Tabouleh *Cracked wheat, parsley and cucumber salad*	$1.79	$3.49
French Fries		$1.99
Onion Rings		$2.49
Pita Chips or Grilled Flatbread		$1.00

Fresh Squeezed Limeade $1.95
Mango Lemonade $1.95

STICKS KeBoB SHOP

Preston Ave: 434-295-5262
Fax: 434-295-9377
Pantops: 434-295-5212
Fax: 434-295-3644
Richmond: 804-282-7010
Fax: 804-282-7015
Williamsburg: 757-903-2675
Fax: 757-903-2678

Source: Company document. Used with permission.

Exhibit 2

Segmentation at Sticks Kebob Shop

Sticks Customer Survey Questions

1. How many times in the last week did you do the following?
    a. Made and ate lunch at home
    b. Brought own lunch to work
    c. Bought lunch at workplace (e.g., cafeteria)
    d. Bought lunch at restaurant/food court/food truck
    e. Skipped lunch and ate a small snack item
    f. Other
2. Please specify the top five restaurants you have visited in the last six months in order of visit frequency.
3. Have you ever visited a Sticks Kebob Shop?
    a. Yes
    b. No
4. How did you first find out about Sticks?
    a. Heard from friend or colleague
    b. Saw in media (print or online—FB, blog, review)
    c. Direct marketing (e.g., Valpak or Groupon)
    d. Noticed from driving or walking by store
    e. Noticed from catering at work (e.g., menu stack)
    f. Noticed at outdoor event/food festival
    g. Other
5. Have you eaten at Sticks in the past three months?
    a. Yes
    b. No
6. In the last month, how often have you visited Sticks for the following occasions?
    a. Weekday lunch
    b. Weekday dinner
    c. Weekend lunch
    d. Weekend dinner
    e. Sticks event (catering at work, food festival)
    f. After-school snack or after-sports practice snack
    g. Other
7. Please indicate how important the following factors are when you visit a restaurant:
    a. Convenient place to eat
    b. Variety of menu options
    c. Good value for the money
    d. Healthy menu options
    e. Food taste and satisfaction
    f. Friendly staff
    g. Pleasant ambiance
    h. Consistency/reliability
    i. Part of the community
    j. Other

Exhibit 2 (continued)

8. Please indicate how you rate Sticks in comparison to similar restaurants that you visit regularly on the following:
    a. Convenient place to eat
    b. Variety of menu options
    c. Good value for money
    d. Healthy menu options
    e. Food taste and satisfaction
    f. Friendly staff
    g. Pleasant ambiance
    h. Consistency/reliability
    i. Part of the community
    j. Other
9. What is your gender?
10. What is your age?
11. What is your approximate average annual household income?
12. How would you best describe your household type?
13. How many children, by age, currently live in your household?
14. In what ZIP code is your home located?
15. In what ZIP code is your work located?
16. Please indicate your best answers to the following:
    a. I tend to plan things very carefully
    b. I sometimes have trouble controlling my spending
    c. I think it is important to purchase products that are made locally
    d. I carefully consider the health benefits of what I eat
17. What is your profession?
18. If you have children living at home, in what activities do they participate?
19. In what activities or hobbies do you participate yourself?
20. In the last month, how many times have you used coupons when you visited a restaurant?
21. How do you find restaurant coupons?

Source: Company document. Used with permission.

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A Practical Guide to Conjoint Analysis

Introduction

Conjoint analysis is a marketing research technique designed to help managers determine the preferences of customers and potential customers. In particular, it seeks to determine how consumers value the different attributes that make up a product and the tradeoffs they are willing to make among the different attributes or features that compose the product. As such, conjoint analysis is best suited for products that have very tangible attributes that can be easily described or quantified.

Although the history of conjoint analysis can be traced to early work in mathematical psychology,[1] its popularity has grown tremendously over the last few years as access to easy-to-use software has allowed its widespread implementation. There have been probably thousands of applications of conjoint analysis in industrial settings.[2] Some of the more important issues for which modern conjoint analysis is used are the following:

1. Predicting the market share of a proposed new product, given the current offerings of competitors
2. Predicting the impact of a new competitive product on the market share of any given product in the marketplace
3. Determining consumers' willingness-to-pay for a proposed new product
4. Quantifying the tradeoffs customers or potential customers are willing to make among the various attributes or features that are under consideration in the new product design

The Anatomy of a Conjoint Analysis

Literally, conjoint analysis means an analysis of features considered jointly. The idea is that, although it is difficult for consumers to state directly how much each feature of a product is worth to them, we can infer the value of an individual feature of a product by experimentally manipulating the features of a product and observing consumers' ratings for that product or choices among competing products.

[1] R. Duncan Luce and John W. Tukey, "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement," *Journal of Mathematical Psychology* 1 (February 1964): 1–27.
[2] Paul E. Green, Abba M. Krieger, and Yoram Wind, "Thirty Years of Conjoint Analysis: Reflections and Prospects," *Interfaces* 31 (May–June 2001): 56–73.

To fix your intuition here, consider the simple example of a sports car. It would be difficult for the average consumer to tell a market researcher exactly how much more valuable a car with 240 horsepower is relative to one with 220 horsepower. It is possible that a consumer might be able to come up with some dollar value, but that value may not really reflect the way that consumer would make choices if faced with a real marketplace situation. Instead, marketers have found that it is much more accurate to present individuals from the target market with a series of cars, described not only by their horsepower but by other attributes as well (e.g., color, price, standard/automatic transmission) and then ask them to rate each of the cars on a numerical scale. Alternatively, the researcher presents several competing cars with different attributes and asks the consumer to choose one. By repeatedly asking the potential customers to rate the cars or choose a car from a competing set, the researcher can infer the value of each individual attribute. This is the essence of a conjoint analysis: replacing the relatively inaccurate method of asking about each attribute in isolation with a model that allows us to infer the attributes' values from a series of ratings or choices.

The Experimental Design

A conjoint analysis begins with an experimental design. This design includes all attributes and the values of the attributes that will be tested. Conjoint analysis distinguishes between attributes and what are generally called "levels." An attribute is self-explanatory. It could be price, color, horsepower, material used for upholstery, or presence of a sunroof, whereas a level is the specific value or realization of the attribute. For example, the attribute color may have the levels red, blue, and yellow, whereas the attribute of the presence of a sunroof will have the levels yes and no. Before a researcher begins to collect data, it is important that all the levels of each attribute to be tested are written down. Commercially available software packages require that the user provides these as input.

Continuing with the car example, an experimental design might look like the information presented in **Table 1**.

Table 1. Example of experimental design.

	Price	**Brand**	**Horsepower**	**Upholstery**	**Sunroof**
Levels	$23,000	Toyota	220 HP	Cloth	Yes
	$25,000	Volkswagen	250 HP	Leather	No
	$27,000	Saturn	280 HP		
	$29,000	Kia			

Source: All tables created by author, unless otherwise noted.

This is a very simple design that contains a total of 15 attribute levels. Real designs often contain more attributes and levels than are presented here.

When constructing an experimental design, it is important to keep the following points in mind:

1. The more tangible and understandable the levels of each attribute are to the respondents, the more valid the results of the research will be. For example, attribute levels such as really roomy are vague, meaning different things to different people, and should be avoided.
2. The greater the number of attribute levels to be tested, the more data that will be needed to achieve the same degree of output accuracy.
3. For quantitative variables (price and horsepower, in this example), the greater the distance between any two consecutive levels, the harder it will be to get a good idea of how a consumer might evaluate something in between the two (e.g., $24,000).

Data Collection

Collecting data for a conjoint analysis has been made relatively simple by the advent of dedicated off-the-shelf software. The exact nature of the data collected is dictated by the type of conjoint analysis that is used. An exhaustive discussion of the benefits and drawbacks of each of the many different types of conjoint analysis now in use is beyond the scope of this technical note. But those interested are encouraged to read Orme for a good discussion of this topic.[3]

The state of the art in conjoint data collection involves using personal computers or a web-based version of the software to guide respondents through an interactive conjoint survey. The software creates the hypothetical product profiles using the experimental design provided by the researcher and estimates the attribute-level utilities from participant ratings or choices.

Interpreting Conjoint Results

Understanding the basic output

The basic results of a conjoint analysis are the estimated attribute-level utilities. Keeping with the example in **Table 1**, conjoint output might look like the output shown in **Table 2**.

Table 2. Conjoint analysis output.

Attribute	Level	Utility (part-worth)	t-value
Price	$23,000	2.10	14.00
	$25,000	1.15	7.67
	$27,000	−1.56	10.40
	$29,000	−1.69	11.27
Brand	Toyota	0.75	5.00
	Volkswagen	0.65	4.33
	Saturn	−0.13	0.87
	Kia	−1.27	8.47
Horsepower	220 HP	−2.24	14.93
	250 HP	1.06	7.07
	280 HP	1.18	7.87
Upholstery	Cloth	−1.60	10.67
	Leather	1.60	10.67
Sunroof	Yes	0.68	4.53
	No	−0.68	4.53

The estimated utilities or part-worths correspond to average consumer preferences for the level of any given attribute. Within a given attribute, the estimated utilities are generally scaled in such a way that they add up to zero. So a negative number does not mean that a given level has negative utility; it just means that this level is on average less preferred than a level with an estimated utility that is positive.

Conjoint analysis output is also often accompanied by t-values, a standard metric for evaluating statistical significance. Because of the way conjoint utilities are scaled, the standard interpretation of t-values can yield

[3] Bryan K. Orme, "Which Conjoint Method Should I Use?," *Sawtooth Software Technical Paper* (2003). A copy of this paper is available at http://www.sawtoothsoftware.com/download/techpap/whichmth.pdf (accessed Apr. 3, 2012).

misleading results. For example, the level Saturn of the attribute Brand has a t-value of 0.87. In general, a t-value of this magnitude would fail a test of statistical significance; however, this t-value is generated because within the attribute Brand, the level Saturn has neither a very high nor very low relative preference. It is basically in the middle in terms of overall preference. Because of the scaling, levels that have more moderate levels of preference within a given attribute are likely to have estimated utilities close to zero, which tends to produce very low t-values (recall that the t-test is measuring the probability that the true value of a parameter is not different from zero).

A better way to think about statistical significance in this context is to examine the t-values of the levels with the highest and lowest preference within a given attribute. An applicable common practice would be if the sum of the absolute value of these two statistics is greater than three, then that given attribute is significant in the overall choice process of consumers. At a practical level, it is rare that an attribute will not be significant, and, if you find one that is, it means it probably should not have been included in the experimental design in the first place, because respondents are not considering that attribute's information when they make choices.

Conjoint Analysis Applications

As mentioned previously, there are many different possible applications of conjoint analysis. We will focus on three very common applications: tradeoff analysis, predicting market share, and determining overall attribute *importances*.

Tradeoff analysis

The utility of any given product that we might consider can be easily computed by simply summing the utilities of its attribute levels. For example, a Toyota with 280 horsepower, leather interior, no sunroof, and a price of $23,000 has a utility of $0.75 + 1.18 + 1.60 - 0.68 + 2.10 = 4.95$. If the car with the same basic specifications were a Volkswagen, the overall utility would drop to $0.65 + 1.18 + 1.60 - 0.68 + 2.10 = 4.85$, a drop of 0.10. This drop can be seen directly by noticing that the difference between the utility for the brand Toyota (0.75) and Volkswagen (0.65) is 0.10. In addition, because nothing else in the profile of the car has changed, this will be the exact utility difference between two cars that are the same except for this brand difference.

A natural consequence of this observation is that we use the utilities to analyze what average consumers would be willing to give up on one particular attribute to gain improvements in another. For example, how much money would they be willing to give up (price) if a sunroof was added to the vehicle? We will now look directly at this issue of the hypothetical car detailed in the previous paragraph. Adding a sunroof to the (Toyota) car would yield an overall utility of $0.75 + 1.18 + 1.60 + 0.68 + 2.10 = 6.31$. This represents an increase in utility of $6.31 - 4.95 = 1.36$ over the identical car without a sunroof.

This information directly implies that we can reduce the utility of price by 1.36, and average consumers would be just as happy as before the sunroof was installed. To find out how much the price can be raised to maintain the same level of utility, we must convert the change in utility with a change in price. We do this by first noting how much the original car costs ($23,000) and the utility associated with that figure, 2.10. We know that we can reduce the price utility by 1.36. This is equivalent to saying that we can reduce the price utility to $2.10 - 1.36 = 0.74$. By referring to **Table 2**, we can immediately see that this implies a price between

$25,000 and $27,000 because −1.56 < 0.74 < 1.15. In fact, if we assume a linear relationship between price and utility in the range between $25,000 and $27,000, we can solve for the exact price by performing a linear interpolation within this range.[4] Specifically, the interpolation yields:

$$\$25{,}000 + \frac{1.15 - 0.74}{1.15 - (-1.56)} \times \$2{,}000 = \$25{,}302.58$$

Utility spread between the two tested price points ($25,000 and $27,000)

Utility spread between $25,000 and the target utility

This implies that, if the sunroof is added, the willingness-to-pay for the average respondent rises from $23,000 to about $25,300. Qualitatively, it shows that the value of a sunroof to consumers is very substantial. Note that this does not imply that the company marketing this particular vehicle could raise the market price by $2,300 if a sunroof is added. While a well-constructed conjoint analysis can provide useful insights into consumers' willingness-to-pay, it does not account for product costs or competitive price responses, both of which are important determinants of price in real-world markets.

This same kind of analysis can be performed for other attributes. We could ask how much additional horsepower we would need to add if the interior was changed from leather to cloth. This particular question does present a problem, however. Because the current vehicle under consideration has 280 horsepower, and that is the maximum amount of horsepower tested by the conjoint analysis, it will be impossible to determine how much consumers will value additional horsepower. This leads to an important consideration when constructing the experimental design. That is, if the output is to be used for tradeoff analysis, it is important that the range of the levels tested within each attribute span the entire range of that attribute before management would ever consider it as a realistic design alternative. If the experimental design takes this into account, we can perform a tradeoff analysis between any two attributes in the design.

Market share forecasting

Another common application is forecasting market share. To use conjoint output for this kind of prediction, two conditions must be satisfied:

1. The company must know the other products, besides its own offering, that a consumer is likely to consider when making a selection in the category.
2. Each of these competitive products' important features must be included in the experimental design. In other words, you must be able to calculate the utility of not only your own product offering but also that of the competitive products.

Market share prediction relies on the use of a multinomial logit model.[5] The basic form of the logit model is

[4] This is a common way to approximate the relationship between the value of the attribute and its utility for attribute values that were not directly tested by the conjoint analysis. The closer the tested levels are to each other, the more accurate this approximation. Also notice that this interpolation can be performed only for quantitative attributes such as price. Interpolating between qualitative attributes, such as brand, is nonsensical.

[5] A good marketing reference to learn about the basics of the logit model is Gary L. Lilien and Arvind Rangaswamy, *Marketing Engineering: Computer-Assisted Marketing Analysis and Planning*, 2nd ed. (Englewood Cliffs, NJ: Prentice Hall, 2002). Also, most econometrics textbooks will have information on logit models.

$$Share_i = \frac{e^{U_i}}{\sum_{j=1}^{n} e^{U_j}},$$

where:

U_i is the estimated utility of product *i*,
U_j is the estimated utility of product *j*, and
n is the total number of products in the competitive set, including product *i*.

To make things clear, consider the following example. Suppose we are interested in predicting the market share of a car with the following profile: Saturn; $23,000; 220 HP; cloth interior; no sunroof. We believe that when consumers consider our car, they will also consider purchasing cars that are currently on the market with the following profiles:

1. Toyota; $27,000; 250 HP; cloth interior; no sunroof
2. Volkswagen; $29,000; 280 HP; leather interior; no sunroof
3. Kia; $23,000; 220 HP; cloth interior; no sunroof

For the Saturn and its associated product profile, the estimated utility is 2.10 − 0.13 − 2.24 − 1.60 − 0.68 = −2.55. Similarly, the utilities of the three competing products can be calculated:

1. −1.56 + 0.75 + 1.06 − 1.60 − 0.68 = −2.03
2. −1.69 + 0.65 + 1.18 + 1.60 − 0.68 = 1.06
3. 2.10 − 1.27 − 2.24 − 1.60 − 0.68 = −3.69

With these utilities in hand, we can now directly apply the logit model to forecast market share for the Saturn. This is given by the following:

$$Share_{Saturn} = \frac{e^{-2.55}}{e^{-2.55} + e^{-2.03} + e^{1.06} + e^{-3.69}} = 0.025 \text{ or } 2.5\%.$$

This implies that this particular Saturn vehicle will achieve a 2.5% market share within the specified competitive set. The market share of any vehicle that can be described by the experimental design and a set of competitive vehicles also described by the experimental design can be found in a similar manner.

Determining attribute importance

A researcher may also be interested in determining the importance of any individual attribute in the consumers' decision processes. Quantifying these attribute importances using the conjoint output is straightforward and can provide both interesting and useful insights into consumer behavior.

Intuitively, the variance of the estimated utilities within a given attribute tells you something about how important the attribute is in the choice process. Take, for example, the attributes Sunroof and Upholstery, both of which have only two levels. If you understand the material up to this point, it should be reasonably clear that Upholstery is a more important attribute than Sunroof. That is because the utility difference between having a sunroof and not having a sunroof (2 × 0.68 = 1.36) is smaller than the utility difference between having leather versus cloth interior (2 × 1.60 = 3.20).

The common metric used to measure attribute importances is

$$I_i = \frac{\overline{U}_i - \underline{U}_i}{\sum_{j=1}^{n} \overline{U}_j - \underline{U}_j},$$

where:

I_i is the importance of any given attribute i

$\overline{U}$ is the highest utility level within a given attribute (subscripts indicate which attribute)

$\underline{U}$ is the lowest utility level within a given attribute.

This equation is really quite intuitive. To calculate the importance of any given attribute, you just take the difference between the highest and lowest utility level of that attribute and divide this by the sum of the differences between the highest and lowest utility level for all attributes (including the one in question). The resulting number will always lie between zero and one and is generally interpreted as the percentage decision weight of an attribute in the overall choice process.

It also should be clear at this point that this estimated attribute importance depends critically on your experimental design. In particular, if you increase the distance between the most extreme levels of any given attribute, you will almost certainly increase the overall attribute importance. For example, if the tested price range was \$21,000 − \$31,000 instead of \$23,000 − \$29,000 (**Table 1**), this is very likely to increase the estimate attribute importance of price.

Let's now consider a concrete example using the attribute Horsepower. The importance of this attribute is calculated as follows:

$$I_{Horsepower} = \frac{1.18 + 2.24}{\left((2.10 + 1.69) + (0.75 + 1.27) + (1.18 + 2.24) + (1.60 + 1.60) + (0.68 + 0.68)\right)} = 0.25$$

In the example, 25% of the overall decision weight is assigned to Horsepower. The reader may verify through analogous calculations that the decision weight for Price is about 27%; Brand, about 15%; Sunroof, about 10%; and Upholstery, about 23%. The numbers provide a very intuitive metric for thinking about the importance of each attribute in the decision process.

Final Thoughts

Conjoint analysis has a broad array of possible applications. Many of these applications are variants of the three very common applications presented here. The increasingly widespread availability of conjoint analysis software—both PC and web-enabled—points to its continued growth as a marketing decision aid.

This note has presented what is generally known as "aggregate-level" conjoint analysis. That is, all the respondents are pooled into one group, and a single set of attribute-level utilities are estimated from the ratings or choices provided by the people in this group. Recent advancements in conjoint analysis have enabled researchers to estimate different utilities for different groups of respondents and even, in some cases, for individual respondents. Although the mathematics necessary for this procedure is sometimes quite complex, it is now possible to estimate the attribute-level utilities and to compute tradeoff analyses for *each individual respondent*. This has some significant advantages over aggregate-level analysis, particularly when considering marketing segmentation issues and analysis of differences in individual consumers' willingness-to-pay for specific product designs. Either way, the data collection and the basic interpretation of the output remain the same. Although there is currently no textbook that can provide answers to all the questions that might arise when applying this technique in a business setting, there is, as of this writing, a very good and surprisingly comprehensive collection of technical papers located on the site of a company that markets conjoint analysis software (https://www.sawtoothsoftware.com/support/technical-papers). These papers provide answers to many of the practical implementation questions a user may face.

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Portland Trail Blazers

We have a new group-sales operation in place and we're looking for dramatic results there.

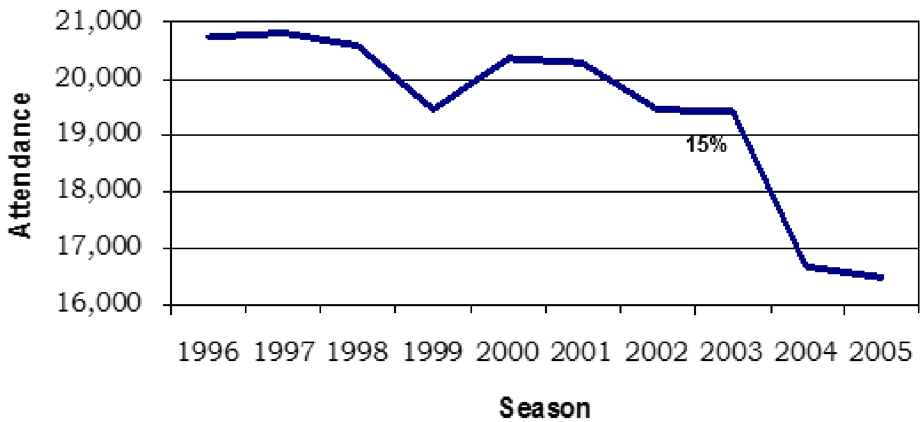
—Steve Patterson, President
Portland Trail Blazers

Less than a month after the 2005 National Basketball Association (NBA) All-Star break, the Portland Trail Blazers were in upheaval. On the court, they had just fired their coach of the past four seasons and were 22–36, in danger of one of the worst seasons in franchise history. Off the court, the Blazers organization was facing considerable challenges as well. The team's home arena, the Rose Garden, had filed for Chapter 11 bankruptcy and was being run by the building's creditors.

The arena, a virtual lock to sell out just three seasons before, had seen attendance numbers fall more than 15% since the 2003 season (**Figure 1**). During the same time, the organization had only been successful in renewing 9 of the 46 luxury-suite contracts that came due in 2005, and 42 of the 70 luxury suites sat empty during the season.[1] Television interest also declined, with a Portland-area Nielsen share of just 5% when the Blazers played the Minneapolis Timberwolves (weather coverage generally received up to 20%).[2]

[1] Todd Murphy, "Have Arena, Need People," *Portland Tribune*, August 10, 2004.
[2] Pete Schulberg, "Blazers Start Losing with Viewers, Too," *Portland Tribune*, January 21, 2005.

Figure 1. Average home attendance, 1996–2007.



Data source: All table and figure data provided by the Portland Trail Blazers.

A similar story was occurring in the sale of the team's "club seats"—special seats for Blazers games that were sold on a multiyear contract and came with club perks. Of 1,800 club seats in 2005, 700 remained available, most of them because subscribers had dropped their contracts during the previous season.

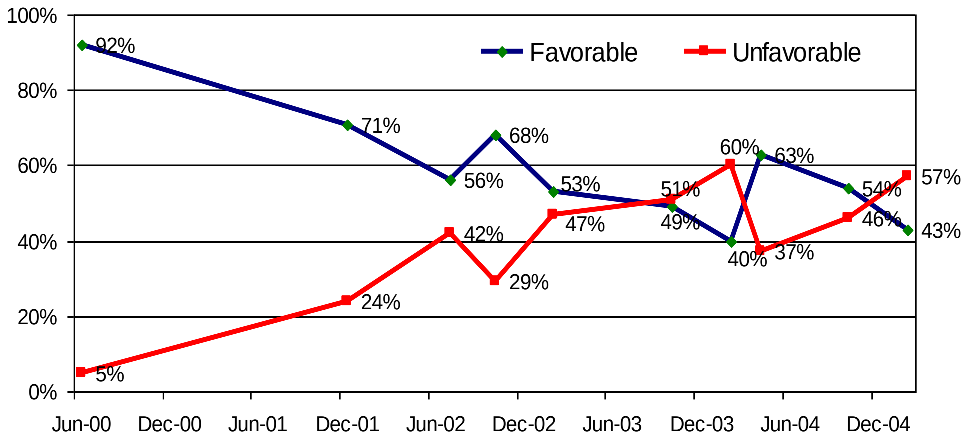
The Portland Sports Market

The Portland Trail Blazers had a monopoly on the professional sports market in Portland, Oregon. Without a dominant university sports program affiliated with the city, the team competed only with minor league baseball and hockey for its share of the city's sporting dollars. At just under two million people in the metro area, Portland was the fourth-smallest market in the NBA.

Each year, the Trail Blazers management tracked Portland-area residents' general perception of the team (see **Figure 2**). The historically strong relationship between the team and the city had soured over the past few seasons, with the percentage of people perceiving the team negatively having increased tenfold since 2000. Fan support had dwindled due to a number of widely publicized player transgressions, including marijuana use, fighting among teammates, and an incident involving animal cruelty.[3]

[3] Andy Giegerich, "Beleaguered Blazers Play by the Numbers," *Portland Business Journal*, October 29, 2004.

Figure 2. Portland-area residents' general perception of the Portland Trail Blazers.



Multigame Ticket Packages

One of the more successful Blazers promotions during the past few seasons had been multigame ticket packages. This program allowed fans to purchase tickets for a number of games at once, and usually included at least one marquee opponent, a game for which individual tickets were difficult to find. The Trail Blazers management saw this program as an effective tool to:

1. Increase ticket sales for less popular games (typically bundled in the package with tickets for hard-to-find games)
2. Increase overall ticket sales because the multigame packages acted as an effective incentive for those who planned on attending only one or two games during the season to increase the number of games they attended
3. Develop more of an ongoing relationship with fans who could potentially become future season ticket holders

Despite the program's relative success, management wanted to explore all potential packages and better understand which options were most popular with fans. The program's goal was to offer a multigame ticket package that had a high appeal to fans while being profitable to the team and not undermining current pricing policies.

Designing the Research Study

The Trail Blazers management team hired Acuity Market Research, a Portland-based research firm, to help design its multigame package study. Together, they determined there were six aspects of the multigame ticket packages that drove a customer's decision to purchase:

1. The team the Blazers were playing
2. The day of the week the game was being played

3. The number of games included in the package
4. The location of the seats
5. The price (per seat) of the package
6. The promotional item included in the package

The project team designed a study utilizing conjoint analysis to ascertain the importance of the individual attributes, as well as the likely response of the market to specific multigame ticket packages. Some things were givens: (1) the high number of teams in the NBA (30 including the Blazers) and (2) the dates of the games included in the package could not be changed. Those attributes would not be included as part of the conjoint products. Instead, questions pertaining to favorite teams and days to watch a game were asked individually, after the conjoint portion of the survey.

An e-mail went out from the Blazers' director of database and Internet marketing to 960 fans who had purchased multigame ticket packages or season tickets in the past but were not current season-ticket holders. The project team decided it was more important to get feedback from people who had already expressed some level of commitment to purchasing Blazers tickets, rather than from general fans of the team and knew it had current e-mail addresses for this group. Although new fans were always purchasing multigame or season-ticket packages, Blazers management believed past purchasers were likely the best prospects for new multigame packages.

The initial e-mail explained the purpose of the study and asked fans to participate. One week later, a reminder e-mail was sent in hopes of increasing the overall response rate of the study. Both e-mails contained a link to an online conjoint-based survey, which included 20 different conjoint choice tasks (an example is included in the **Appendix**), Blazers-specific questions, and a battery of demographic questions. Most respondents took between 10 and 15 minutes to complete the survey.

Participants were given a chance to win free tickets to Blazers games, as well as autographed Blazers items, such as jerseys, basketballs, and posters, for taking part in the survey.

Study Findings

The e-mail solicitations received a total of 204 valid responses (a 21% response rate). Summary statistics regarding demographics and past Blazers-game attendance are located in the **Appendix**.

Acuity began its analysis of the multigame packages by computing the attribute-level utility scores to help better understand the stand-alone preference of each of the individual attribute levels. The utility score data are shown in **Table 1**.

Table 1. Utility score data.

Utility	Number of Games
0.03257	3-game create-your-own pack, including 1 elite team and 2 very good teams
0.24383	6-game create-your-own pack, including 2 elite teams and 4 very good teams
–0.2764	10-game create-your-own pack, including any combination of teams.
Utility	**Ticket Price**
0.65646	$15 per seat per game
0.22011	$25 per seat per game
0.126	$35 per seat per game
–1.00257	$60 per seat per game
Utility	**Ticket Location**
–0.73169	300 level, behind the baskets
–0.43716	300 level, on the corners
0.15736	300 level, midcourt
1.01148	200 level, midcourt
Utility	**Promotional Item**
0.12511	Priority for home playoff tickets
0.17428	Hot dog and soda with each ticket
0.00158	Trail Blazers apparel (hat, jersey, etc.)
0.01689	$20 gift certificate for popular local restaurant
−0.31786	No promotional item

While the conjoint study allowed all the attributes and levels to be randomly assigned, in reality, Blazers management was unwilling to allow certain price and seating combinations—no matter how well received they were—due to the cost structure of the arena. It disallowed:

- 200-level seats for less than $60
- 300-level midcourt seats for less than $25

Cost of Multigame Packages

While the fan preference was extremely important to Blazers management, any multigame packages the group designed had to be financially attractive and align with the organization's strategic goals. Each of the multigame-ticket-package attributes had costs and strategic implications associated with it:

Number of games: Blazers management preferred the six-game package because it offered the capability of pairing the most popular teams with games that were more difficult to sell tickets to (weekday games, less competitive teams, etc.). Its next preference was a 10-game package, because it allowed the team to efficiently sell a large number of the remaining games to a single fan.

Seat location: Although nearly all the Blazers' stadium costs were fixed expenses, the organization still applied a cost to each of the seat locations in the stadium. This cost structure had to be met, at a minimum, for any tickets that were sold and differed based on seat location. Minimum seat pricing is shown in **Table 2**.

Table 2. Fixed costs based on seat location.

Seat Location	Fixed Cost
300 level, behind the baskets	$10.00
300 level, on the corners	$12.00
300 level, midcourt	$18.00
200 level, midcourt	$40.00

Promotional items: A direct cost was associated with each of the Blazers promotional items offered to fans. For example, if a hot dog and soda were offered with each Blazers ticket, the team would have to pay the Rose Garden's vendor services a negotiated price of $3.25 per package. The $20 gift certificate to a popular restaurant was purchased for a negotiated price of $10. The restaurateur deeply discounted the gift certificates in exchange for the marketing exposure.

The only promotional item without a direct cost was offering priority for home-playoff tickets, given that the tickets were still sold at full retail price and multigame ticket holders only received priority in purchasing available tickets. **Table 3** presents the unit cost of each of the potential promotional items.

Table 3. Cost of promotional items.

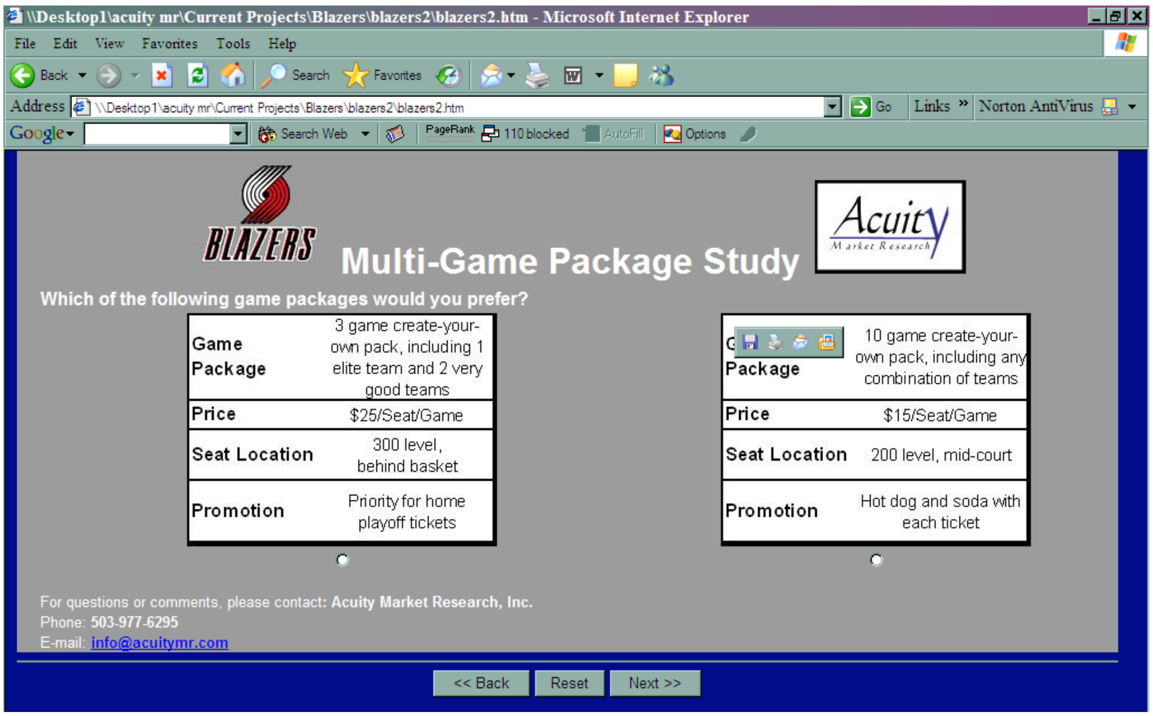
Promotional Item	Cost
Priority for playoff tickets	$0.00
Hot dog and soda with each ticket	$3.25
Trail Blazers apparel (hat, jersey, etc.)	$12.00
$20 gift certificate to a popular restaurant	$10.00

Utilizing the conjoint information, in addition to the other data available from the survey, the Blazers management team felt prepared to design the multigame package it believed the fans would most prefer. What attributes were most important to the fans? What should the Blazers' multigame package include? Should there be more than one? How profitable would each of the packages be?

Appendix

Portland Trail Blazers

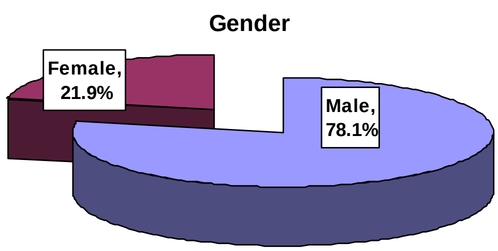
Example: Online Conjoint Survey

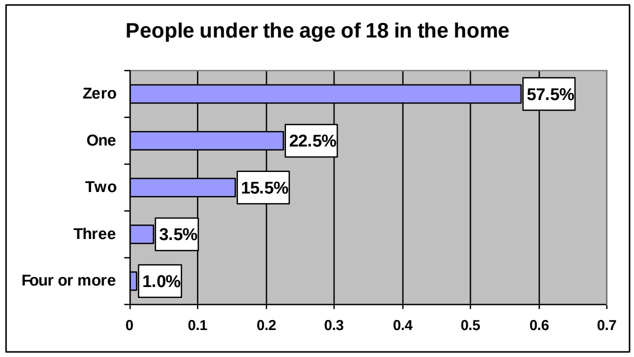


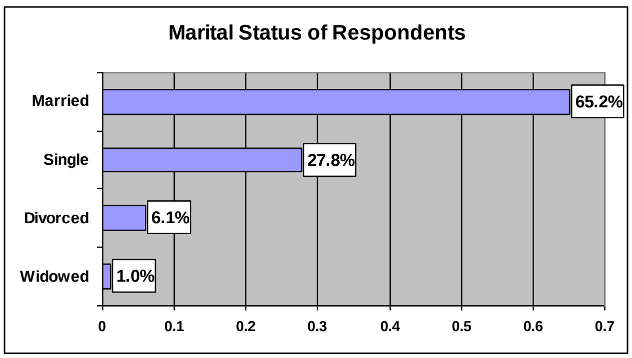
Source: Appendix items provided by the Portland Trail Blazers.

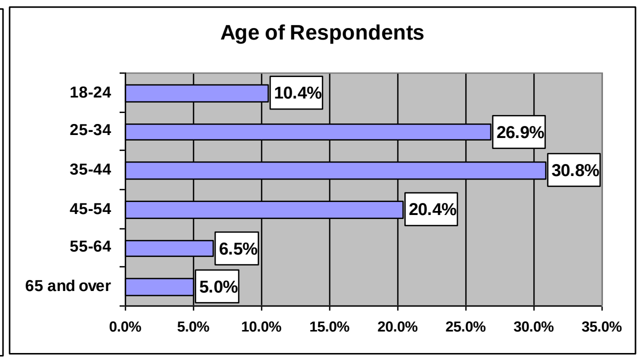
Appendix (continued)

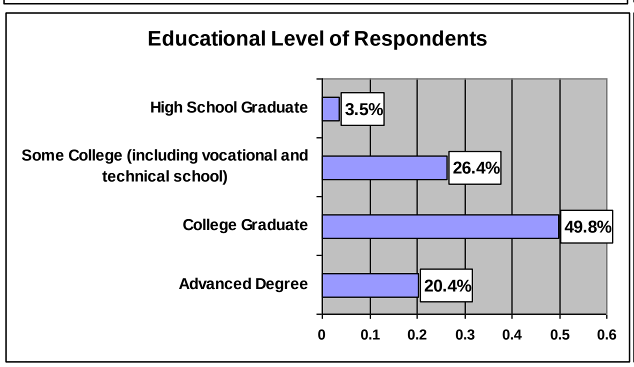
Study Demographics

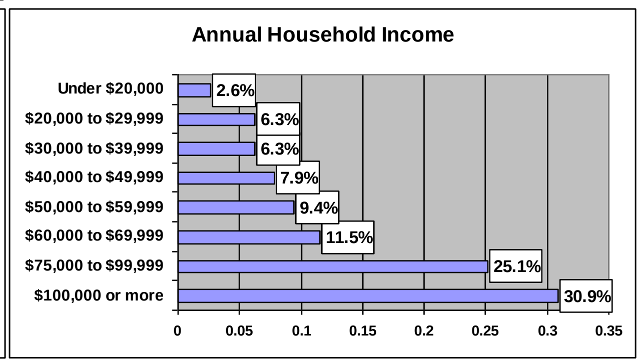












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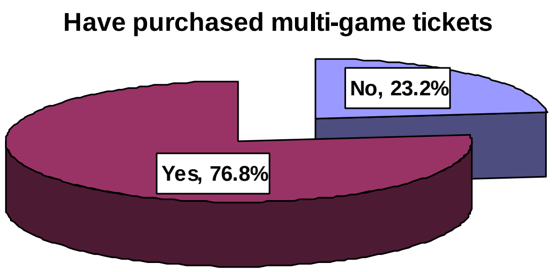
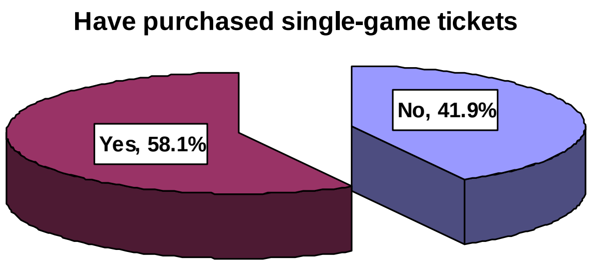
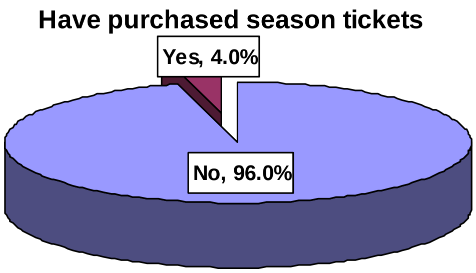
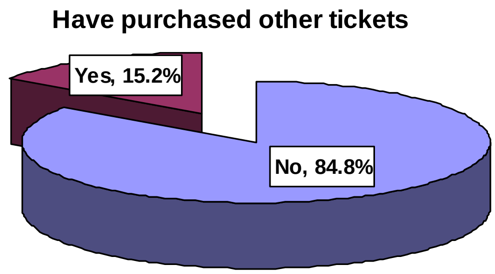
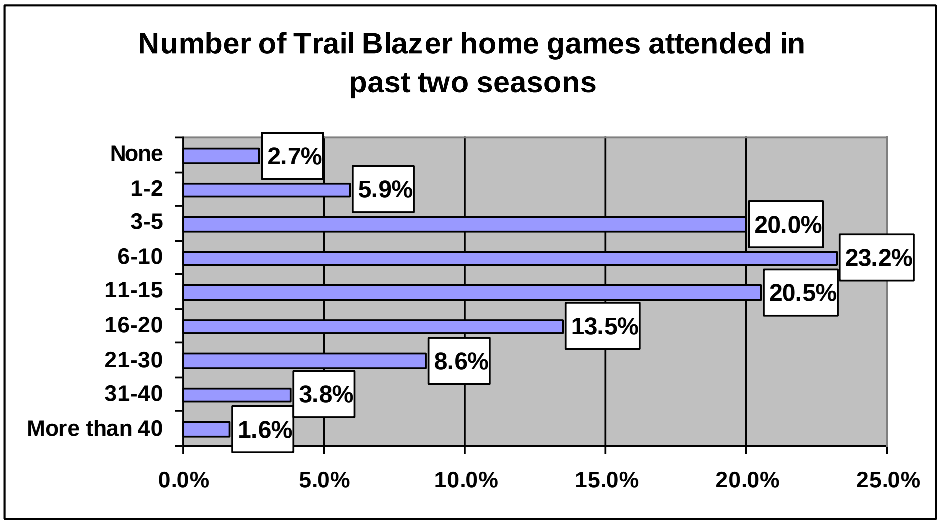
Game Attendance Behavior











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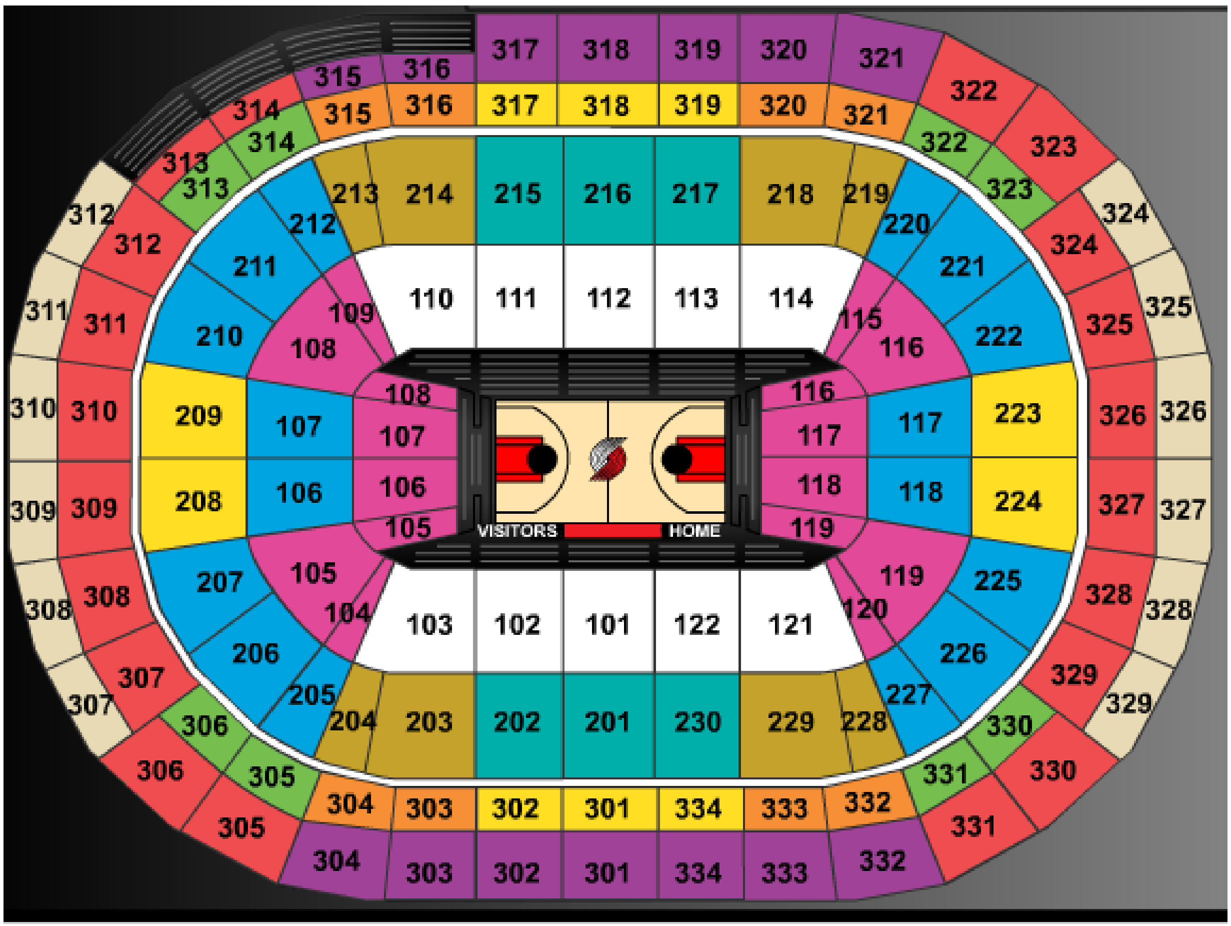
Rose Garden Seating Chart



MULTIPLE REGRESSION IN MARKETING-MIX MODELS

The movie *Moneyball* has a lot to teach us about optimizing a company's marketing mix. In the movie, the management of the Oakland Athletics discovers that the baseball team can get ahead by changing its perspective and looking at data differently than its competitors.

The A's know most major-league teams use batting average (hits over real opportunities) as the prevailing metric for determining the worth of a hitter. Traditional baseball wisdom says, "You hit more, you win more." So the players who have more hits per at bat are generally the most sought after and are paid the most money.[1] But by examining the outcome of decades of baseball games, the A's manager finds a variable he believes to be more predictive of success. It is not only hits that help a baseball team win; walks count too. Getting on base and not making outs is more closely correlated with winning games than hits alone.

The team's management takes the analysis of the data and uses it to buy undervalued players—players who don't necessarily have the highest batting averages but who do have high on-base percentages. For a small-market team such as the A's, which has less money to spend on players than other franchises, this strategy changes the game.

Moneyball is about baseball, but the idea also works in the context of business marketing. Although management often makes assumptions, by actually analyzing the data, a business can better understanding how to succeed. And if a business can find an important variable before others begin using it, management can build its strategy around that variable to gain an advantage.

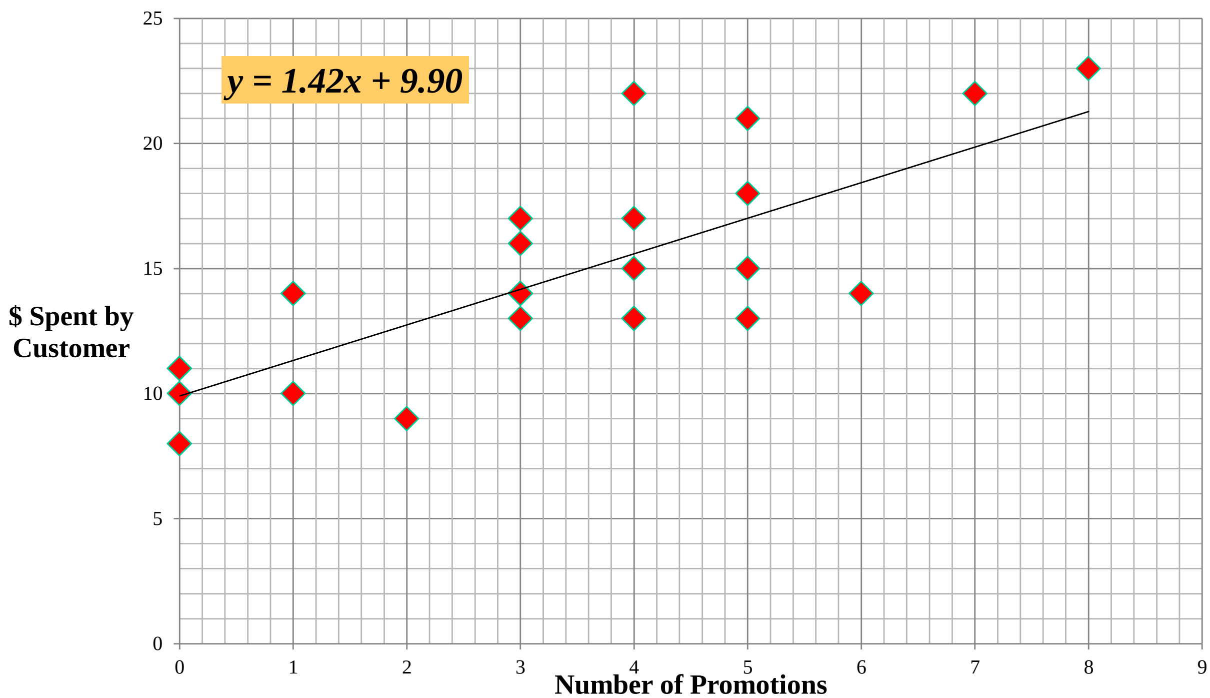
[1] *Webster's Third New International Dictionary*, *Unabridged*, defines "at bat" as "an official turn at batting charged to a baseball player except when the player walks, sacrifices, is hit by a pitched ball, or is interfered with by the catcher."

Reviewing Single-Variable Regressions for Marketing

Single-variable regression analyses allow us to predict outcomes using one variable. While such analyses are often oversimplifications of real-world marketing problems, it is necessary to understand them before moving on to more illustrative multivariable analyses.

Consider the following common marketing-mix example for a hypothetical company, No More Germs, which sells toothpaste. In order to determine the relationship between the number of promotions the company does and the number of units it sells, the company plots its known data on an *x*–*y* plane (**Figure 1**). On the *x*-axis, the company plots the number of promotions (i.e., price reductions) it could have in a month. On the *y*-axis, No More Germs plots the number of purchases made by customers for each given number of promotions.

Figure 1. Illustration of single-variable regression.



Source: All figures created by case writer unless otherwise specified.

In this example, No More Germs has data covering a time period of 29 weeks, promotions ranging between 0 and 9, and corresponding sales from 10 to 23. A linear, single-variable regression analysis can be run on this data with the aid of computer software.[2] The results will help No More Germs examine the relationship between the number of promotions

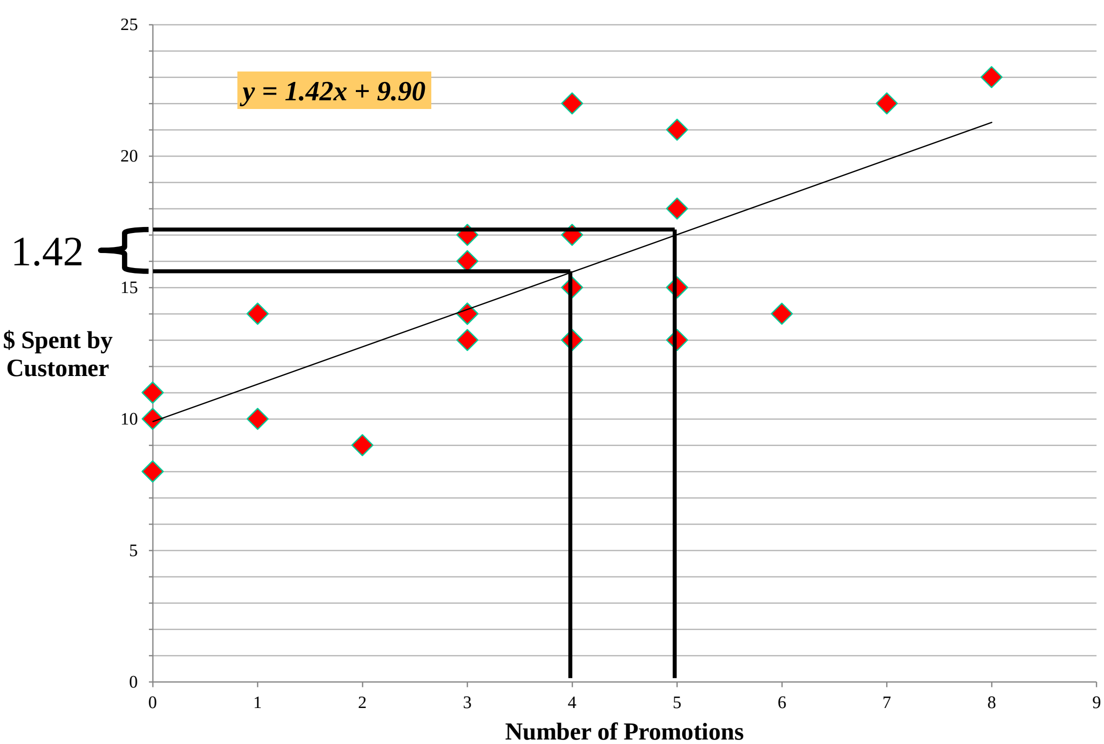
[2] For more information on how to perform a regression using computer software, visit Darden Marketing Analytics at http://dmanalytics.org/.

and the number of sales to customers by producing a function that describes the relationship. The objective is to draw a line that at each point represents the number of sales that are likely for any given number of promotions. In this case, the *x* variable—or independent variable—is the number of promotions. The *y* variable—or dependent variable (known as such because it depends on *x*)—is units sold.

The function produced by the regression is intended to cover as many of the known data points as possible and/or reduce the distance between the line and the points as much as possible. This will allow the data analyst to accurately predict sales that are likely, given the number of promotions in other sample sets of data (in this case, if data from other weeks are used). The equation from the regression analysis for the best-fit straight line for No More Germs is $y = 1.42x + 9.9$.

The most critical outputs of the regression for the marketing manager are two coefficients: the intercept (9.9) and the slope (1.42) of the line. The intercept represents the number of sales that are likely when promotions are 0, which is equal to 9.9 in this example. This is the point where the line crosses the *y*-axis. The slope of the line describes the relationship between sales (*y*, or the dependent variable) and promotions (*x*, or the independent variable) by stating the ratio of the change in *y* to a unit change in *x*. In our example, the number of sales changes 1.42 per one-unit increase in promotions (**Figure 2**). The slope (often referred to as "rise over run") is therefore 1.42 ÷ 1, or 1.42.

Figure 2. Illustration of slope in a single-variable regression.



Three things can be determined immediately by looking at the slope of the line: (1) If the number is positive, the relationship between the two variables is positive, meaning as the independent variable increases, so does the dependent variable; (2) if the slope of the line is 0, no changes are observed in the dependent variable as the independent variable changes (in other words, the variables are not correlated); and (3) if the slope of the line is negative, a change in the independent variable will produce the opposite effect in the dependent variable (i.e., No More Germs' sales would decrease if promotions increased).

Remember that while in this case, the relationship between promotions and sales is obvious, in most cases, a regression analysis is used to show a relationship between variables that are not as clearly related. For example, what if No More Germs wanted to know what kind of effect web advertising had on sales of its products? The company's marketing manager might not know how effective web ads are compared with print ads, for example, and the regression would assist him or her in deciding where to put the company's advertising dollars.

The output of No More Germs' sample regression (which is typical of these reports) is shown in **Figure 3**. While the analysis yields multiple statistics, the most critical for marketing analysts (in addition to the coefficients of the equation) are R-squared and P-value. In this example, R-squared is 60%, meaning the line described by this function is appropriate for explaining 60% of the data points. This indicates how accurate the function is within the current sample of data. (Note: A typical marketing-focused regression would have an R-squared of about 20% to 30%, as there are numerous factors that affect sales—such as competition, weather, and so on—that would be unknown before running the analysis.)

Figure 3. Illustration of output from single-variable regression analysis.

Regression Statistics	
Multiple R	0.775
R Squared	0.601
Adjusted R Squared	0.586
Standard Error	2.566
Observations	29

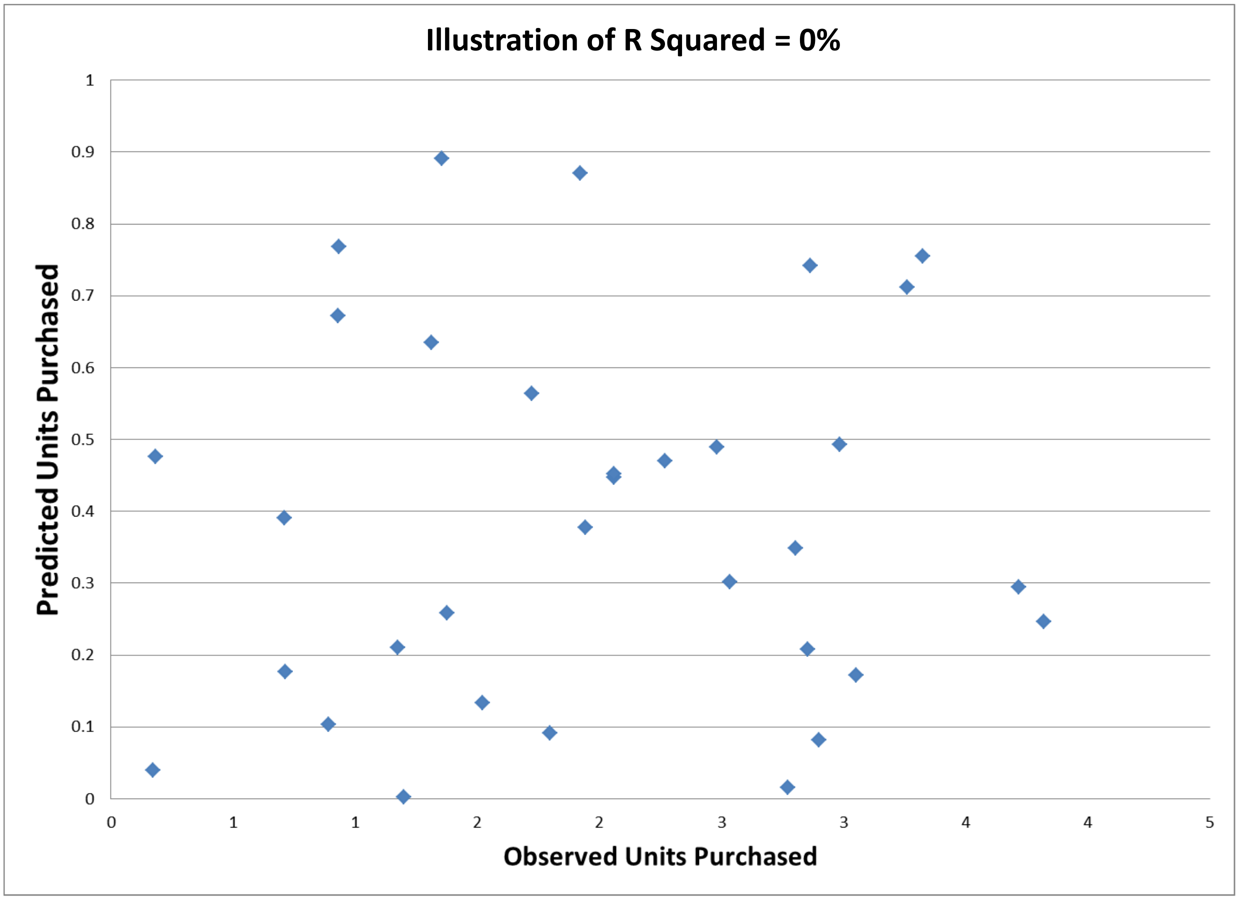
ANOVA

	df	*SS*	*MS*	*F*	*Sig F*
Regression	1	267.28	267.28	40.60	0.00
Residual	27	177.75	6.58		
Total	28	445.03			

	Coefficients	*SE*	*t-Statistic*	*P-value*
Intercept	9.90	0.85	11.60	0.00
Number of Promotions	1.42	0.22	6.37	0.00

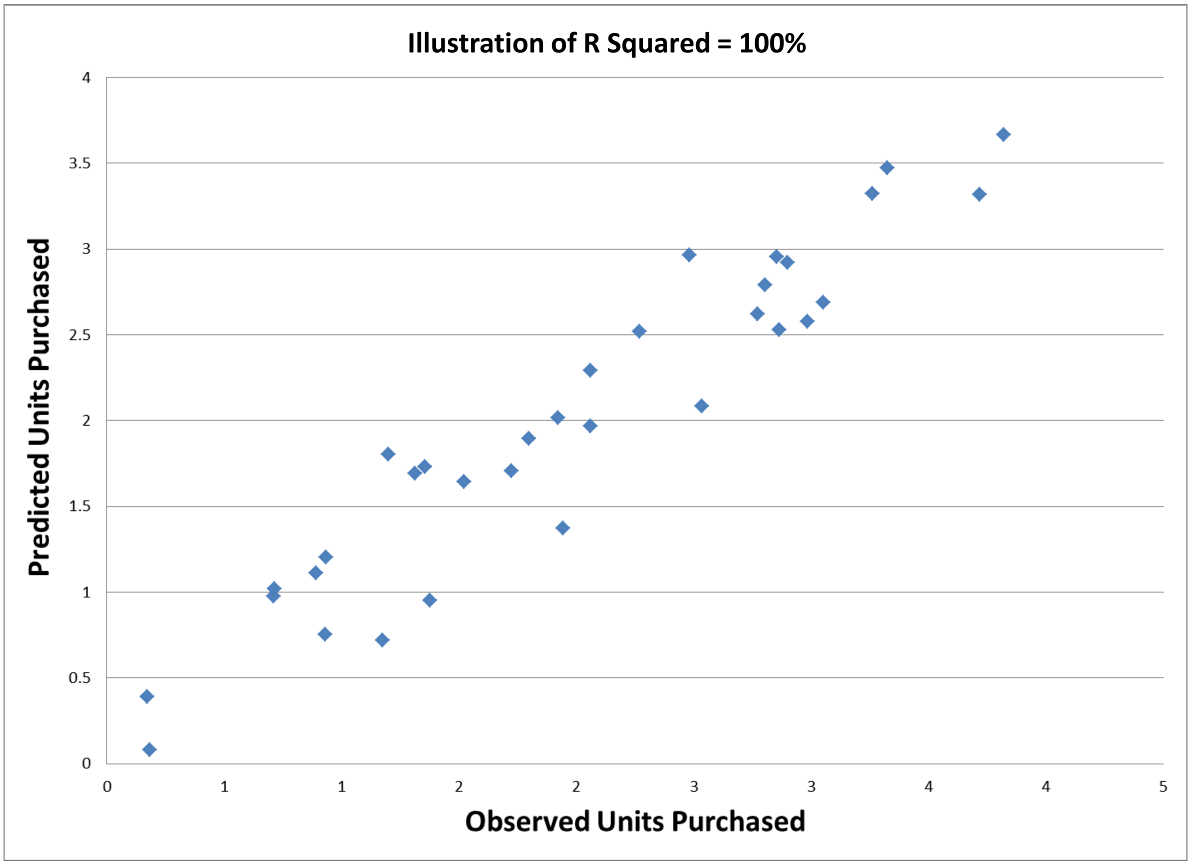
To better understand the meaning of R-squared, imagine your regression output indicates an R-squared of 0. The resulting plot will look like a disorderly circle of data (**Figure 4**).

Figure 4. Illustration of R-squared = 0%.



A line cannot be produced that will explain any of the data. Now imagine R-squared is 100%. In this case, all of the data points (dots) will be on a line (**Figure 5**). The line accounts for all of the points in the data set. All regression analyses will result in lines with accuracy somewhere in between these extremes.

Figure 5. Illustration of R-squared = 100%.



P-value describes the significance of the findings given the sample size. But what does "significant" mean? In this population sample, 29 observations are made. Because this is a regression analysis of a small sample, we want to know whether we will still see the resulting coefficients if we include another 29 observations or another 29,000 observations. Will the slope of the line be 1.42, or will it be 0 or negative? Here, the P-value indicates there is a 0% chance the coefficients will change beyond the standard error given the addition of more data points or different samples. Most important, it indicates a 0% chance the slope will become negative, indicating the opposite relationship between the variables than what is indicated by the regression. In other words, regardless of how many times the data are sampled, the relationship will hold.

In addition to these critical outputs of a regression analysis, it may be beneficial to be familiar with one other value. In this example, t-stat is a reflection of P-value; however, depending on the regression or model used, the name of this value may change (e.g., chi-square). P-value, on the other hand, will always be referred to in the same way. Particularly for marketing managers, who in most cases will need to be smart consumers of regression outputs but will not have to run the analyses themselves, P-value will provide adequate information about the significance of the findings.

Adding Variables to the Regression

Now let us consider an analysis of the effects of multiple variables on the number of units purchased by hypothetical consumers. When marketing managers work through a problem, they have to gather data in order to find a solution. In this case, we are going to start with a solution (i.e., a true model) and use only data that we know are a part of that model to determine how effective a regression can be at predicting outcomes.

The data shown in **Figure 4** reflect an analysis of three variables: price paid, whether the unit was on feature (highlighted in a mailer or other promotion but not necessarily at a reduced price), and whether the unit was on a store display (on an endcap or stand-alone cardboard cutout). In this case, we know the true effect of each of these variables on the outcome because we created the model. This is evidenced by the fact that we have an R-squared of 99% (with the 1% error inserted randomly in the true model we created).

Because this is a hypothetical situation, the data are known to coincide with the true model (**Figure 5**), in which the intercept is 6.22, the price coefficient is −2.28 (meaning the slope is downward and, as price increases, sales decrease), the feature coefficient is 0.38, and the display coefficient is 0.22 (meaning the slope is upward and, as feature and display increase, sales increase). Also, because this is the true model, R-squared is 0.99, indicating an extremely low chance of error.

But imagine you are a marketing manager, and you don't have access to the true model. (In fact, no one can know the true model in any real-world situation.) Looking only at the data, you must approximate the true model as closely as possible. Imagine now that you don't think price is important in your model, and consider only feature and display. As shown in **Figure 5**, the resulting coefficients describing the effect those variables have on units purchased are higher than in the true model.

Since you would not have access to the true model in a real-world situation, what would these results influence you as a manager to do? You would expect that feature and display would be more effective than they, in fact, are and invest more heavily in those marketing strategies. As shown in the true model, however, price has a great effect on units purchased, and the effects of feature and display are therefore overstated in the estimated model.

To correct such a bias, intuition comes into play. First, a good marketing manager should know from experience that price has a significant effect on units purchased. A good marketing manager should also know that when items are on feature and display, they tend to come with a reduced price. In other words, price and feature/display tend to be negatively correlated.

This is what is known as an omitted-variable bias, because the estimated model has not taken into account a variable that has a significant effect on what is being measured. While such biases may not always be as obvious as in this example, they are common in multivariable regression analyses, and this is the main point of differentiation when moving away from single-variable analyses (which are by nature oversimplified and, at least in terms of marketing, fail to fully explain most real-world situations).

To ensure a bias is not detrimental to the findings of a regression analysis, we must examine the direction of the bias. In this case, the bias is positive because feature and display have a higher coefficient in the estimated model than in the true model. But how do we know the direction of the bias if we do not know the true model? Again, some intuition and experience are necessary. We know price and sales have a negative correlation. We know price and feature and price and display also have a negative correlation. The direction of the bias when price is the omitted variable is the product of the sign of the correlation between price and units purchased and the sign of the correlation between price and feature and display. The product of a negative and a negative is a positive, so in this case, the bias is positive (**Figure 6**):

Figure 6. Correlation between independent and dependent variables.

	Price	**Feature**	**Display**	**Units Purchased**
Price	1	(0.25)	(0.24)	(0.98)
Feature		1	(0.09)	0.45
Display			1	0.32
Units Purchased				1

Direction of Bias in Feature =

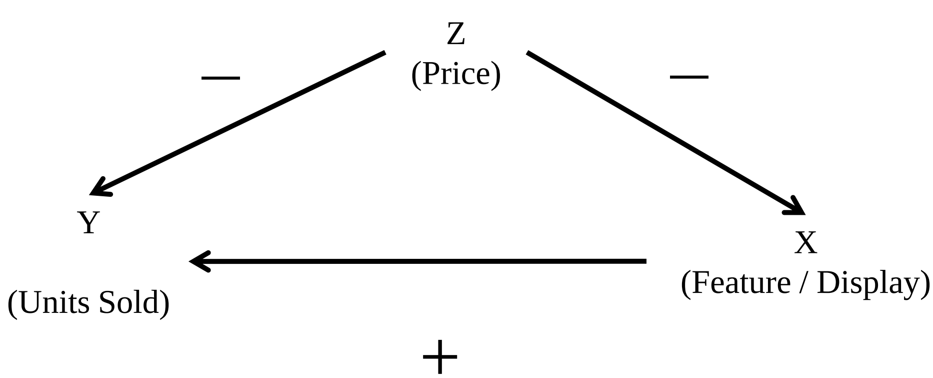
[sign of correlation between price & units]
*
[sign of correlation between price & feature]

	price	**bias**
units	**− ve**	
feature	**− ve**	**+ ve**
display	**− ve**	**+ ve**

Note: – ve = negative; + ve = positive

Another way to think about omitted variables is shown in **Figure 7**. Here, *x* and *y* are shown with respect to some omitted variable, *z*. By examining this relationship, the marketing manager can determine the direction of the bias created by omitting that variable.

Figure 7. Illustration of omitted variable bias.



Note that an omitted variable is only a problem when it affects both whatever is included in the model and the dependent variable. If it is not correlated with other independent variables in the model, removing it will reduce R-squared, but it will not affect the coefficient of the variables included in the model. In the current example, the variation in units is being assigned to feature and display, when in fact it should be assigned to price. If the changes in one variable did not affect another, whatever variation in the dependent variable was being captured would still reflect reality. For example, weather can have a profound effect on sales (e.g., a hurricane keeping buyers in Florida from making it to stores for an extended period), but hurricanes need not necessarily affect the feature or display plans for a brand. If weather and feature and display plans are not correlated, then inclusion of weather is not necessary to obtain accurate estimates of feature or display.

In this example, we have what is known as an optimistic model, which can be a concern for marketing managers. When presenting such results to decision makers, the findings will be overstated because a significant variable (price) was omitted. Although you cannot include everything in your model, knowing whether the results are conservative or optimistic is beneficial. Typically, a conservative model (one that has a negative bias) is best. Investing in a marketing channel shown to be effective by a conservative model may still represent lost opportunity if the amount of the investment is low, but it will not represent an outright mistake in resource allocation.

When do you know if you have the true model? You never know, but examining the four Ps (product, price, place, and promotion) is a good place to start. The results of a regression analysis are only hypotheses, and they should be tested in field experiments in order to ensure their validity.

Economic Significance: Acting on Regression Outputs

There are two types of significance: statistical and economic. Statistical significance is related to the P-value or statistical significance, which indicates whether the relationship observed in a sample is likely to be observed in the population, as well. A P-value less than 0.1 is typically considered statistically significant.

But how do you know when it makes economic sense to invest in the findings of a regression? As a marketing manager, you must ask yourself if the benefit of a marketing intervention (i.e., the size of the coefficient) justifies the expense. This is what is known as economic significance.

Consider the single-variable-regression example in which we examined promotions versus purchases. The benefit provided from one promotion was found to be an increase in number of sales of 1.42. This was found to be a statistically significant finding. To determine economic significance, you must weigh this benefit against the cost of doing a promotion, taking into account the gross profit from the sale of a single unit.

Let us assume that the gross profit per unit is $5, and the cost of a promotion is $0.50. Therefore, profit = (units purchased × gross profit) − (cost of promotion × number of promotions), or (**Equation 1**):

$$\text{Profit} = 1.42 \times 5 - 0.50 \times 1 = 7.1 - 0.5 = 6.6. \quad (1)$$

In this example, the company will make $6.60 per promotion. But if the cost of the promotion increases or the company makes less gross profit per unit, the economic significance of the promotion could quickly be lost. In other words, even if your regression findings are significant, you must first use a profit/loss function before taking action.

Conclusion

A regression analysis is intended to help marketing managers understand the relationship between two or more variables or concepts. Typically, a company will use historic sales data or data generated through experiments to identify factors that most affect a brand's sales.

The value of a regression model is only as good as the variables selected to be in the model. Strong managerial intuition is required to identify variables (such as price, feature and display, among others) that are most closely related to sales. For the best results, managers should also have some insight into how these variables actually relate in the real world to determine whether the results of a regression might be conservative or overly optimistic. This intuition is the artistic or creative side of analytics and is necessary to move a regression beyond a statistical exercise and turn it into something valuable for a business.

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DESIGN OF PRICE AND ADVERTISING ELASTICITY MODELS

Introduction

The marketing mix that a manager may deploy can affect the sales of a product and can be categorized under the traditional four Ps of marketing (product, price, promotion, and placement). But the perennial question managers face concerns the combination of these different marketing-mix variables that will give them maximized sales, highest share, lowest inventory, or maximized margins. Quite often, these questions are answered by historical data: for example, past sales or market share for different levels of expenditures on these marketing-mix variables. In this note, we consider the design of models that allow managers to obtain robust price and advertising elasticity estimates.

Consider the following scenario: Belvedere vodka was introduced in the United States in 1996. This vodka traced its roots back to the Warsaw suburb of Żyrardów, Poland, and its production process went back more than 600 years. Lately, it had begun to observe a decline in its overall share of the vodka market. The company suspected the cause to be new market entrants that were capturing market share with effective advertising. To sustain the growth rate and defend its share from the competition, Belvedere was considering two options: increasing its advertising expenditure and/or reducing the pricing. Such a scenario is very common for most brands during the various stages of their brand (or product) life cycles. The first step toward solving this issue is to estimate the elasticity of a brand to its price and advertising.

Price Elasticity of Demand

Pricing is one of the most critical variables that marketers have problems with. Based on common sense, consumers tend to buy more of a product as its price goes down, and using the same logic, they will buy less if the price goes up. Price elasticity of demand (**Figure 1**) is a measure to show the responsiveness of the quantity demanded of a good (or service) to a change in its price; it gives the percentage change in quantity demanded in response to a 1% change in

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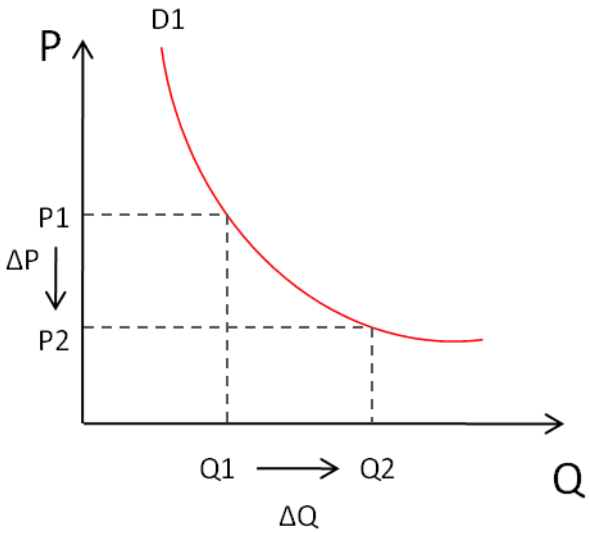
price (holding constant all the other variables in the marketing mix).[1] A product with a price elasticity above 1 is said to be elastic, as changes in demand are relatively large compared with changes in price. Correspondingly, a product whose elasticity goes below 1 is deemed inelastic.

Figure 1. Price elasticity of demand.



Price elasticity can be derived as the ratio of change in quantity demanded (%ΔQ) and percentage change in price (%ΔP).

Source: Created by case writer.

Price elasticity of demand (PED) can be calculated using **Equation 1**:

$$\text{PED} = [\text{Change in Sales} \div \text{Change in Price}] \times [\text{Price} \div \text{Sales}] = (\Delta Q \div \Delta P) \times (P \div Q) \qquad (1)$$

Or if we have a sample of historical sales and price data, then we can regress the sales against price, and the coefficient of this regression will give price elasticity as shown in **Equation 2**:[2]

$$\text{PED} = \text{Coefficient of price when } Ln(\text{sales}) \text{ is regressed on } Ln(\text{price}) \qquad (2)$$

Here, we are assuming that the *Ln*-*Ln* model (i.e., dependent *Ln*(sales) regressed on independent *Ln*(price)) gives us a better linear model, which historically has been the case with most models, such as that in **Equation 3**:

$$Ln(\text{sales}) = \alpha_1 + \beta_1 \times Ln(\text{price}) + \varepsilon_1 \qquad (3)$$

where β_1 represents the price elasticity in the above case and ε_1 is the random error term drawn from a normal distribution (the standard assumption in a linear regression model).

[1] This is essentially never the case—as will be explored in more detail later in this note.

[2] The coefficient and price elasticity are by definition not the same, but they are very closely related to each other, and in most cases, the coefficient is a close proxy for the elasticity.

Assuming consumers are rational and reasonably informed, the coefficient (and hence the price elasticity) should be negative. Therefore, the phrase “greater price sensitivity” means more negative price elasticity, and similarly “less price sensitivity” means less negative price elasticity.

Refer to **Exhibit 1** for Belvedere’s sales and price data and the regression results. With a regression coefficient of −1.259, we can say that price elasticity of sales for Belvedere is high (i.e., its customers are fairly price sensitive). Reducing price may have a positive effect on sales. This model suggests that a price decrease of 1% may result in 1.259% sales increase of 9L cases of Belvedere vodka.

Advertising Elasticity of Demand

The advertising elasticity of demand (AED) is a measure of the responsiveness in the demand of a product to changes in the level of advertising. It can be calculated by using **Equation 4**:

$$\text{AED} = [\text{Change in Sales} \div \text{Change in Advertising}] \times [\text{Price} \div \text{Advertising}] = (\Delta Q \div \Delta A) \times (A \div Q) \quad (4)$$

Let us suppose that the total advertising exposure in period 1 was \$100 and total sales were 200 units. Then, in period 2, the advertising was increased to \$125 and the total sales were 300 units. Here, an advertising spend increase of \$25 resulted in a sales increase of 100 units. So, AED = (100 ÷ \$25) × (200 ÷ \$100) = 8. In other words, a 1% increase in advertising results in an 8% increase in sales. Similar to the procedure for price elasticity, the basic formulation to estimate advertising elasticity is to run a regression of log of sales (or market share) on log of advertising. The coefficient of the log of advertising will be the estimate of advertising elasticity (**Equation 5**):

$$Ln(\text{sales}) = \alpha_2 + \beta_2 \times Ln(\text{advertising}) + \varepsilon_1 \quad (5)$$

where β_2 is the advertising elasticity of demand and ε_1 is the random error term drawn from a normal distribution.

All other factors remaining equal, an increase in advertising is expected to result in a positive shift in demand and hence a positive advertising elasticity. AED can be utilized by a firm to make sure its advertising expenses are in line, though an increase in demand may not be the only desired outcome of advertising.

Refer to **Exhibit 2** for regression results of Belvedere’s sales and advertising data. A regression coefficient of −0.013 and low t-stat value suggest that changing advertising expenses may have no effect on Belvedere’s sales or that the change cannot be predicted. Elasticities (or sensitivities) can be used for short-term advertising effects[3]—values less than 0 imply negative returns to advertising and greater than 1 imply the firm is underadvertising. So the value should range from 0 to 1. In our simple regression model above, we took advertising expenditure as one simple independent variable by combining expenditures for all possible media. But different media (e.g., print, display, in-store, television) may have varied effects on the demand of a product based on its characteristics. More analysis is required to study the effect of different media, and if required, more than one variable should be incorporated in the regression model to get a better-fitting model and help the marketing manager decide on the advertising expenditure—both the total amount and its distribution across different media.

Building a Comprehensive Model

If both PED and AED are significant, the regression model should include both price and advertising as independent variables (**Equation 6**):

$$Ln(\text{sales}) = \alpha + \beta_1 \times Ln(\text{price}) + \beta_2 \times Ln(\text{advertising}) + \varepsilon_1 \qquad (6)$$

"Bias" is a commonly used term to describe the effect of omitted variables. It is used where there are systematic differences in the estimated elasticity (due to errors in estimation, not environmental differences) and the true elasticity in the market. This bias may be caused by omission of variables, which may be correlated with those included in the equation. The decision to include or omit certain variables in the model other than price and advertising will therefore depend on the correlation of a variable with the dependent variable and its correlation with other independent variables. If advertising elasticity is higher than the true value, then it is said to be a positive bias, but if it is lower than the true value, then it is called a negative bias. Conversely, if price elasticity is more negative than the true value, then it is said to be a positive bias, and if it is less negative, then it is called a negative bias (see **Figure 2**).

[3] In the case of multiplicative models, the coefficients were elasticities, whereas in the case of linear models, elasticities can be estimated by multiplying the regression coefficient by the ratio of means of the dependent variable and the advertising measure.

Figure 2. Building a model.

If the true model is as follows:

$Ln(Y) = \alpha_0 + \alpha_1 \times Ln(\text{price}) + \alpha_2 \times Z + \varepsilon$,

but we estimate the model to be

$Ln(Y) = \beta_0 + \beta_1 \times Ln(\text{price}) + \varepsilon$,

the true value of coefficient β_1 will be the sum of the estimated coefficient β_1 and the bias

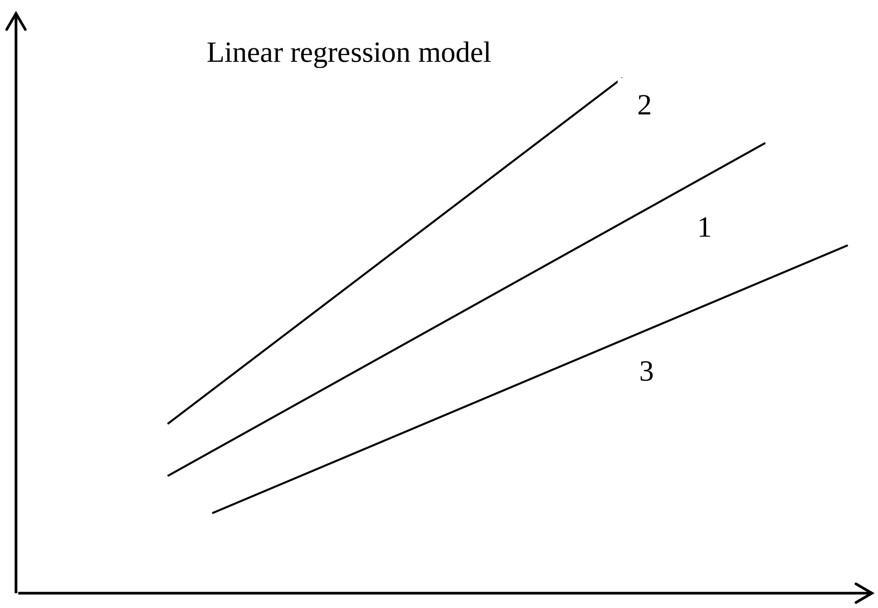
$\beta_1^{true} = \beta_1 + \text{bias}$.

If r is the covariance between independent variables, Ln(price) and Z,

then the bias can be proven to be the product of the coefficient of the omitted variable (α_2) and some function of covariance of independent variables [$f(r)$]:

Bias = $\alpha_2 \times f(r)$.

- If the dependent variable is not related to the omitted variable, then there is no bias (=0).
- If the included independent variable (here, Ln(price)) is not correlated to the omitted variable (covariance is zero), then there is no bias (=0).
- If α_2 (correlation between the omitted variable and the dependent variable) and r (covariance between independent variables) are of same sign, then the bias is positive.
- If α_2 and r are of different signs, then the bias is negative.



1 = true model, with all variables included

2 = estimated model with omitted variables—positive bias

3 = estimated model with omitted variables—negative bias

Source: Created by case writer.

The following sections detail some major factors that would need to be included in a comprehensive marketing-mix model for price and advertising elasticity.

Product quality

If consumers are even minimally informed about the product quality, then the better-quality product would be able to command higher prices. With this assumption, the correlation coefficient for a regression model on price and quality will be positive. Therefore, if higher-quality products also sell more, the omission of quality from the model would lead to positive bias of price elasticity. This means that the estimated price elasticity in a model without product quality would be more negative than a model that includes product quality.

Distribution

The more widely the product is available to customers, the better the sales of that product. But the relationship between distribution and price (and between distribution and sales) is not straightforward. Firms with high-priced brands typically have selective (or exclusive) distribution channels. If this strategy holds, the omission of distribution would lead to less negative price elasticity (i.e., a negative bias).

Brand life cycle

As a brand matures, consumers' knowledge about that brand (e.g., deals, prices, comparables, availability) increases. Also, the early adopters of a brand are less price sensitive. Therefore, price elasticity tends to increase (i.e., become more negative) over the life cycle of a brand.

Time series data versus cross-sectional data

Price elasticity for a brand will have two components: (1) a within-brand component, a measure of sensitivity to prices of a particular brand over time and (2) a between-brands component, a measure of sensitivity to differences between brands. Because consumers mostly respond to prices at the point of purchase, using only a snapshot of data across brands without any time variation leaves out the within-brand component of elasticity. If the within-brand component is weak (less negative), then this sort of data aggregation over time would lead to a positive bias in price and advertising elasticity. Price elasticity would be more negative and advertising elasticity would be more positive if the model used data across brands for a single time period. When prices and advertising are included over time, it is better if the frequency of the time series reflects the product's purchase cycle. For example, for consumer packaged goods, the price and advertising elasticities are more accurate if the sales, pricing, and advertising decisions are sampled every week so that they are reflective of consumer's typical grocery trip frequency.

Carry-over effect of advertising

Advertising rarely has an immediate effect on sales. If we take into account the effect of advertising on sales for the current period, more often than not, those effects would be in the form of spikes and they would be relatively small (i.e., quite fragile) as compared with other marketing variables. Some research indicates that the current effect of price is 20 times larger than the current effect of advertising. The portion of advertising that retains its effect and affects consumers even beyond the period of its exposure is known as the carry-over effect. Depending on the product type, consumer segment, and firm's strategy, there could be several reasons for this carry-over effect: delayed consumer response due to their backup inventory, delayed exposure to the ad, shortage of retail inventory, and so on. Therefore, to account for the total effect of advertising, include both the current effect and all the carry-over effect.

The Koyck model provides a way to capture the carry-over effect of advertising: It enhances the basic linear marketing-mix model, by including a lagged dependent variable as an additional independent variable. So, as per the enhanced model, sales of the current period depend on sales of the prior period and all the independent variables that caused prior sales, plus the current values of the same independent variables.

If the original model (before Koyck) was as shown in **Equation 7**:

$$Ln(Y_t) = \alpha + \beta_1 \times Ln(A_t) + \beta_1 \times B_t + \varepsilon_t \tag{7}$$

then **Equation 8** is the enhanced model (by Koyck):

$$Ln(Y_t) = \alpha + \lambda \times Ln(Y_{t-1}) + \beta_1 \times Ln(A_t) + \beta_1 \times B_t + \varepsilon_{t.} \tag{8}$$

In this model, β_1 captures the current effect of advertising, while $\beta_1 \times \lambda \div (1 - \lambda)$ can be calculated to be the carry-over effect of advertising. The higher the value of factor λ, the longer the effect of advertising will be. Similarly, the smaller the value of λ, the shorter the effects of advertising will be (i.e., sales depend more on current advertising). The total effect of advertising is the sum of current and carry-over effects; that is, $\beta_1 \div (1 - \lambda)$.

If the advertising effects are positively correlated from one period to the next (i.e., the last period's advertising has a positive correlation with current period's advertising), and if the past advertising has a positive correlation with the current period's sales, then the omission of the carry-over effect will result in a positive bias.

Contextual factors

Another factor that may come in to play is the disposable income of consumers in a region where a product is being sold. Consumers in countries (or regions) with high disposable income may be less price sensitive. If so, then higher income would lead to lower price elasticity (i.e., less negative). At the same time, better-informed customers in a region (as well as stronger regulations and antitrust laws) may lead to increased price sensitivity.

Overall, the exogenous variables (e.g., GNP and sociodemographics such as average family income, family size) generally have a positive correlation with sales, and their exclusion could have a positive bias on the model. The regional context may also have a correlation with advertising, for example, due to differences in preferences, production cost structures, and restrictions.

Table 1 summarizes the effect of bias due to the omission of different variables from the marketing mix:

Table 1. Effect of bias in price and advertising elasticity.

Factor	**Bias in Price Elasticity**	**Bias in Advertising Elasticity**
Product Quality	+	
Distribution	–	
Brand Life Cycle—Early	+	
Absolute Sales	+	
Time Series	–	–
Include Carry-over		+
Contextual Factors (income, family size, etc.)		+

Source: Created by case writer.

Other factors to consider while designing the model include:

Promotion

Promotional activities can take one of two forms: (1) increasing product awareness through displays, campaigns, demonstrations, and so forth or (2) incentivizing consumers to try a company's products through coupons, rebates, and so on. Normally, firms tend to run the incentive programs along with their strategy of charging higher prices: higher prices for existing customers and rebates to acquire new customers. In such a case, prices and promotions would be positively correlated. On the other hand, the other form of promotions (increasing awareness) is generally used concurrently with lower prices. The goal is to maximize consumer awareness, and in this case, the prices and promotions would be negatively correlated. In either case, inclusion of promotion characteristics is necessary to obtain a better distinction between price effects and promotion effects on sales.

Competition

The price elasticity tends to be more sensitive if the firm compares the price of its products with that of its competitors. Consumers tend to consider relative price rather than absolute price when opting for a specific brand. Therefore, an increase in price may not negatively affect sales if the competition also raises prices in the same period. Following the same logic, if a firm fails to respond to a price change from the competition, the choice may affect its sales (negative for price decline by competition and positive for price increase).

Share versus volume

If sales volume is used as a dependent variable and advertising as independent, sales may be gained from a competitor (existing market) and sales may be gained from new customers (market expansion due to advertising). But if instead of sales, market share is used as a dependent variable, market expansion is eliminated as a possible reason.[4] As a result, the models using share (instead of sales) should normally have smaller elasticity.

Conclusion

A marketing-mix model can be a strategic asset for a firm. Developing a good model requires knowledge of advanced statistics as well as a deep understanding of consumer behavior and the business context. Response models provide a good tool to aid marketing-mix decisions. They give managers a way to assess the relative importance of their different marketing-mix options. The product line may be the most effective marketing-mix option, followed by distribution, price, and promotion.[5] Managers should, however, be aware that response models assume that the market a company will face in the future would remain unchanged as compared with the past (or the time frame used to estimate the advertising and price elasticities). Price and advertising elasticities are an accurate reflection of consumer preferences, competitor reactions, the number of brands, firm strategy, and other market factors during the time of data collection. Expectations of returns from a firm's marketing-mix decisions must be informed by anticipated competitor actions and changes in the consumer preferences and competitive landscape. For this reason, it would also be a good idea to periodically update the marketing-mix models and re-estimate price and advertising elasticities.

[4] With market share as a dependent variable, the effect of advertising will appear in both numerator and denominator.

[5] Berk M. Ataman, Harald J. Van Heerde, and Carl F. Mela, "The Long-Term Effect of Marketing Strategy on Brand Sales," *Journal of Marketing Research* 47, no. 5 (2010): 866–82.

Exhibit 1

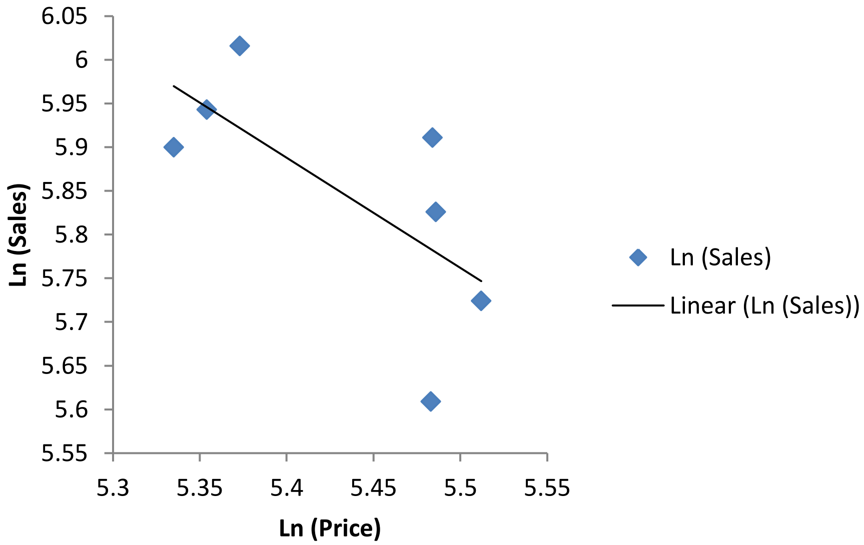
DESIGN OF PRICE AND ADVERTISING ELASTICITY MODELS

Regression of *Ln*(Sales) versus *Ln*(Price)

Year	**Sales (thousands of units)**	***Ln*(Sales) (thousands of units)**	**Price (dollars)**	***Ln*(Price) (dollars)**	**Advertising (thousands of dollars)**	***Ln*(Advertising) (thousands of dollars)**
2007	410	6.016	215.44	5.373	20486.1	9.93
2006	381	5.943	211.45	5.354	2923.5	7.98
2005	365	5.900	207.45	5.335	4826.3	8.48
2004	369	5.911	240.87	5.484	13726.6	9.53
2003	339	5.826	241.33	5.486	10330.2	9.24
2002	306	5.724	247.55	5.512	13473.6	9.51
2001	273	5.609	240.48	5.483	9264.6	9.13

Regression Statistics	
Multiple R	0.67536
R Squared	0.45611
Adjusted R Squared	0.34733
Standard Error	0.11269
Observations	7

	Coefficients	*Standard Error*	*t-Stat*	*P-value*
Intercept	12.686	3.340	3.798	0.013
Ln (Price)	−1.259	0.615	−2.048	0.096



Source: Created by case writer.

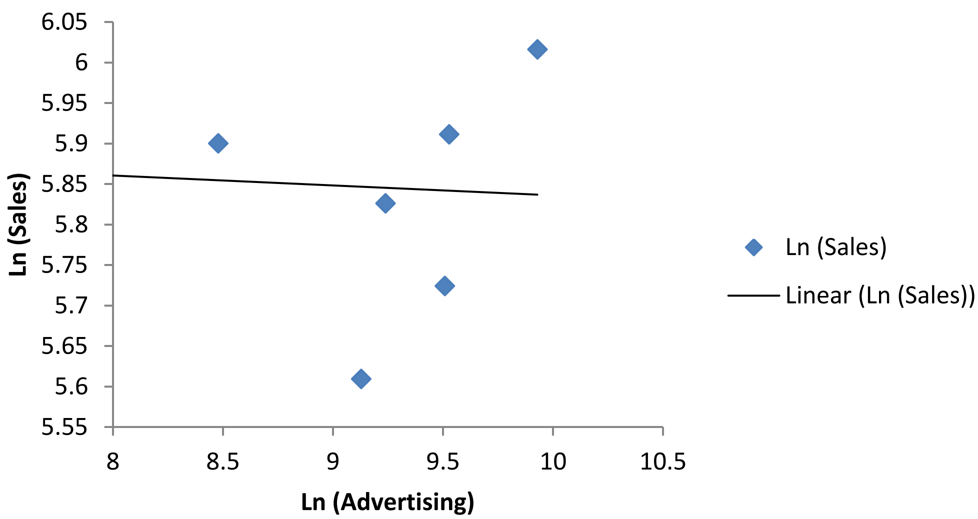
Exhibit 2

DESIGN OF PRICE AND ADVERTISING ELASTICITY MODELS

Regression of *Ln*(Sales) versus *Ln*(Advertising)

Regression Statistics	
Multiple R	0.06102
R Squared	0.00372
Adjusted R Squared	−0.19553
Standard Error	0.15252
Observations	7

	Coefficients	*Standard Error*	*t-Stat*	*P-value*
Intercept	5.963	0.850	7.018	0.001
Ln (advertising)	−0.013	0.093	−0.137	0.897



Source: Created by case writer.

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SVEDKA Vodka (A)

As he waited for his wife to meet him, Guillaume Cuvelier sat in a downtown Manhattan restaurant sipping vodka straight up. As founder and managing director of Spirits Marque One, a liquor importer, Cuvelier wondered if patrons of such an upscale bar would soon be ordering his new vodka by its name: SVEDKA. It was mid-1998, and the product was set to launch in just a few months. Scanning the bar for the competition's vodka bottles, Cuvelier ran through the marketing campaign in his head.[1]

The U.S. government defined vodka as a neutral spirit "without distinctive character, aroma, taste, or color." As one food and beverage writer explained, "Good vodka is considered to be one without the harsh, rubbing-alcohol fumes of ethanol."[2] The now-popular liquor originated in the 14th century in either Russia or Poland (depending on which history you believe) as a spirit distilled from rye or wheat. In the early 1800s, the introduction of filtration and dilution techniques allowed vodka to evolve into something more refined but no less potent.

As Cuvelier enjoyed his drink, the image of James Bond came to mind—described years earlier by an industry observer as "the first upscale vodka drinker."[3] Consumers were increasingly imitating Bond's discerning taste for high-priced vodka. In this climate, Cuvelier reviewed his own pricing, distribution, and positioning one last time. He hoped he was right that the vodka market was ready for a midpriced option. He wondered if there really was an opportunity below the Bond tier and above the very low-priced products. With a small marketing budget, Cuvelier had to be correct in his efforts to position his brand as he created a new segment.

On Trend

Trends in the marketplace inspired Cuvelier to take a closer look at opportunities in the spirits business (whiskey, gin, and vodka were among those classified as spirits). In 1991, he had received his MBA from the Darden School of Business at the conclusion of a two-year hiatus from his position with LVMH's Möet Hennessy-Louis Vuitton.

[1] Case writer interview with Guillaume Cuvelier, October 13, 2008; unless otherwise indicated, all subsequent attributions derive from this interview.
[2] Corby Kummer, "Flavorless No More," *Atlantic Monthly,* December 2004.
[3] William Grimes, "Summer Places: The Super Vodkas," *New York Times,* June 2, 1991.

As an industry insider during the 1980s and early 1990s, Cuvelier had been inspired by Absolut vodka's success as a product, brand, and category leader. "Pre-Absolut, you could say that vodka was vodka was vodka," he said.

Cuvelier believed there was room to compete in the category by offering his own twist on the concept of name-brand vodka. With that purpose in mind, in 1998, Cuvelier founded a small entrepreneurial team of industry experts in New York City. That same year, vodka was the top-selling distilled spirit, representing 24% of total spirits consumption in the United States, up 3.6% in volume sales from 1997. The growth in premium vodka was in stark contrast to the negative long-term trend for most other spirits. (See **Exhibit 1** for vodka sales from 1975 to 1998 and projections for the category.)

The Market

Branded vodka dated back to the late 1860s, when Smirnoff cultivated the endorsement of the czar, engaged in comparative advertising with competitors, and paid patrons of Moscow bars to demand Smirnoff and accept no substitutes. Russia's connection with the category became prominent in the minds of many consumers. A leading imported vodka from Russia, Stolichnaya, had been introduced to the United States as recently as 1965. The brand leveraged its Russian image, evoking a strong connection to its origin and heritage. But "Stoli stumbled after the Soviet downing of Flight 007 in 1982, [which] hurt sales of many Russian products."[4] Once a Russian import, Smirnoff was eventually produced in the United States and came to dominate the domestic vodka segment, capturing almost 20% of the market share by 1998. Until the launch of Absolut, Smirnoff dominated the premium-price vodka segment with a brand name that derived authenticity from the family's Russian heritage.

The launch of Absolut in 1979 and its now-famous ad campaign helped the brand attain its pop-culture status. In 1998, Absolut spent $18 million on advertising.[5] Years later, *USA Today* reported: "Absolut had pioneered selling distilled spirits on image, persuading consumers to buy prestige in a bottle for $20. But the new prestige vodkas, at $25 to $200, have become what Absolut was 20 years ago."[6]

It took more than a decade for the Dutch Ketel One and American Skyy (then the only domestic vodka priced above $10) to enter the market. New prestige vodkas available at a high price point did indeed seem to become what Absolut once was. *The Business of Spirits* stated that the price for vodka "increased to $30 with the debut of Grey Goose, Chopin, and Belvedere in the late 1990s. Now, the debut market [was] flooded with $30 vodkas."[7]

The success of Grey Goose proved people would pay $30 for a bottle of vodka; in 1998, its sales increased 50% from the previous year.[8] Cuvelier had watched as "consumers became increasingly aware about the look, quality, and origin of vodka." (**Exhibit 2** shows the number of new vodkas introduced from 1996 to 1998.)

[4] Kummer.
[5] *Adams Liquor Handbook 1999* (New York: Adams Business Media), 122.
[6] Theresa Howard, "Absolut Puts a New Premium on Vodka," *USA Today,* March 30, 2004.
[7] Noah Rothbaum, The Business of Spirits: How Savvy Marketers, Innovative Distillers, and Entrepreneurs Changed How We Drink (New York: Kaplan Publishing, 2007), 46.
[8] Adams Business Media. Note: Grey Goose received a 96 on the Beverage Testing Institute's well-regarded 100-point scale from the Beverage Testing Institute.

Smirnoff was not alone in its high-volume sales and market share results. Brands such as Popov, Gordon's, McCormick, and Barton (each priced under $10) sold the most cases and enjoyed the largest shares.[9] A significant portion of these sales was for the larger-size plastic bottles.

Cuvelier believed that a midpriced vodka could capture some volume sales from the under-$10 market. "This standard vodka category had never been expanded to include consumers who were willing to stretch their wallets a little bit," he said.

The Product

Vodka could be manufactured inexpensively out of many different raw ingredients and didn't need to be aged. Its standard alcohol content was 40% or 80 proof. Because the staple ingredients were relatively cheap, vodka companies invested in more complex distilling and filtering methods as well as flavor ingredients to distinguish their brands. Marketing campaigns often highlighted "more exotic backstories" to justify higher prices and profits.[10] Indeed, vodka's smoothness and thickness could vary from brand to brand. "The burn is usually associated with inexpensive vodkas," said Robert Plotkin, founder of BarMedia, a beverage consulting firm.[11]

Cuvelier was dedicated to creating a high-quality product that could be distinguished for its soft, silky drinkability. He selected Lidkoping, Sweden, as the manufacturing site. Cuvelier knew the country had recently joined the European Union, causing it to deregulate the alcohol monopoly. "My plan was to be the first to effectively develop and produce 80-proof Swedish vodka immediately after the reopening of the market," he explained. "I wanted the vodka to be from Sweden, so I could take advantage of the Absolut tailwind."

SVEDKA outsourced its production to large, established industrial facilities. The glass bottles were imported from Germany, decorated in France, and shipped to the factory in Sweden to be filled with vodka. The finished product was shipped in cases to the United States.

Wine Enthusiast confirmed the quality of Cuvelier's product, rating SVEDKA 93 out of 100. Classifying the vodka as a "Best Buy," the review said, "We can't remember using the word 'complex' when describing a vodka before, but this one shows a tightly knit set of characteristics that deserve applause."[12]

SVEDKA would initially be available in the standard 750 mL and 1.75 L bottles. Larger and smaller sizes could be added once the business grew. "This gradual size rollout was common industry practice, especially for a start-up brand," Cuvelier said. While many brands were extending their selection to include flavored vodkas, SVEDKA focused on its core unflavored product for the launch.

The Price

In addition to the option of imitating the premium prices of recent imported vodka successes, there was the under-$10-per-bottle market, which Cuvelier estimated was approximately 80% of the market volume (also known as the "standard" vodka segment, it ranged from $5 to $9 for 750 mL). In fact, in 1998, 23

[9] Adams Liquor Handbook 1999, 132.
[10] Rothbaum, 45.
[11] Jim Rendon, "Want to Profit From Vodka?" New York Times, October 31, 2004.
[12] "Best Buy," *Wine Enthusiast*, 1999.

million cases were purchased at retail prices less than $10 per 750 mL bottle (**Table 1**).[13] And then there was the third opportunity: to be a midtier player between the high and low price spectrums.

Table 1. Vodka category price, units sold, market share, and launch year by brand, 1998.

Brand	Price (750 mL)	Cases (9 L) (in thousands)	Market Share (percentage)	Launch Year
Grey Goose	$25.00	50	0.2	1997
Ketel One	18.00	450	1.3	1989
Absolut	16.00	3630	10.6	1979
Stolichnaya	16.50	1,100	3.2	1970
Skyy	11.50	702	2.1	1993
Smirnoff	10.00	6,720	19.7	1960
Gordon's	7.00	2,155	6.3	1960
Popov	6.50	2,230	6.5	1960

Note: Market share calculation is based on total case volume for imported and domestic vodka.

Data sources: Adams Business Media; Virginia Department of Alcoholic Beverage Control; case writer estimates.

Exhibit 3 shows the supplier case prices for vodka. In 1998, according to a Standard & Poor's survey of the alcohol industry, operating margins for U.S. alcohol beverage companies were about 20%, "well above the 12% to 14% range for packaged food companies."[14]

Cuvelier estimated that wholesaler margins for SVEDKA averaged 25%. Retailers' margins varied from 30% to 35%.

It was industry practice to offer retailers volume discounts. Cuvelier created **Table 2** to estimate the discount levels he would be expected to offer.

Table 2. Estimated discount levels based on case quantity discount.

Discount Level	Case Quantity Discount	Estimated Sales	Savings to Retailers
1	3	10%	8%
2	5	15%	13%
3	25	75%	19%

Source: SVEDKA.

To reach a final everyday suggested retail bottle price, Cuvelier had to consider the costs along the wholesale and retail channels. The wholesaler's net laid-in costs were the sum of the free on board (FOB) price, the U.S. Federal Excise Tax (FET), state tax, and freight costs. (The FET per proof gallon was $13.50 in 1998.) SVEDKA classified the mandatory FET and individual state taxes (which varied by state) as hard production costs.

Pricing was tricky, and critics warned Cuvelier that if the price were too low, consumers might think the vodka was low-quality. But if SVEDKA were priced too high, consumers might question its value. A midrange price would risk SVEDKA's getting lost among the more premium brands. Already, higher-priced brands were encountering competition from the superpremium competitors. In *The Business of Spirits,* author Noah Rothbaum commented on the dilemma SVEDKA faced: "Many companies with high-priced spirits are

[13] M. Shanken Communications, "Distilled Spirits Study," *Impact,* 2000.
[14] *Industry Surveys: Alcoholic Beverages & Tobacco,* Standard & Poor's 166, no. 10 (March 5, 1998): 8.

concerned that their products soon will be leapfrogged by other, even more expensive brands, stealing their attention and market share."[15]

Target Customer

Despite the risks he identified, Cuvelier was optimistic. "I believe that SVEDKA is the only brand in the vodka category to bridge the two ends of the category, appealing to both upgraders and consumers looking for the best possible value," he said. "I see SVEDKA as being at the crossroads of the market." SVEDKA wanted to capture the new vodka drinkers as the category was expanding, along with the "upgraders" who were looking for an opportunity to drink something better than the standard offerings. SVEDKA could be the vodka of choice for both price-driven groups.

In addition to considering consumer price sensitivity, Cuvelier segmented vodka drinkers into two large groups based on age and consumption behavior. Regular vodka drinkers tended to be price-conscious and loyal to a brand; consumers in this first segment were mostly older males. The second group consisted of the 21-to-35-year-old consumer, who represented 40% of the vodka market. (**Exhibit 4** shows the breakdown of distilled spirits drinkers by category and age group.) Cuvelier thought this target group was also price-conscious, but not so brand-loyal. He was confident that SVEDKA, if positioned properly, would be able to tap into this younger crowd.

Distribution

Off-premise (or off-trade) channels were the liquor and retail stores, while on-premise (or on-trade) channels included bars, hotels, and restaurants. Brands were usually launched simultaneously in both the on-trade locations and retail outlets. The on-premise percentage of volume was higher for premium brands because consumers often ordered drinks mixed with a specified brand-name vodka. For example, in 2003, 51% of Ketel One's volume was from on-premise. The percentages of on-premise consumption for Grey Goose, Absolut, and Stoli were 48%, 38%, and 37%, respectively.[16]

The spirits industry was a highly regulated business. Producers and importers could not sell directly to the retailers; instead, they were required to sell to licensed liquor wholesalers, who then serviced retailers. Licenses were issued by the state and therefore restricted wholesaler distributors from operating beyond any given state's jurisdiction. Cuvelier relied on a small internal sales team to manage the distributors as key clients. By leveraging relationships within the industry, "I tried to overcome the biggest hurdle of getting distributors on board," he said.

Another obstacle in distributing liquor was the issue of control states (also known as monopolies). In 18 U.S. states, accounting for about 25% of the population, state governments exercised monopoly control over the wholesaling and/or retailing of alcohol (**Exhibits 5** and **6**). These states, among them North Carolina, Vermont, and Washington, were scattered across the country. Michigan, Pennsylvania, Washington, and Virginia were not only control states but also ranked among the top 15 states for retail spending on distilled spirits.[17] Most control states had higher taxes and prices than noncontrol states. For marketers, obtaining distribution meant persuading each independent state liquor commission to carry their brands.

[15] Rothbaum, 163.
[16] SVEDKA corporate presentation.
[17] *Adams Liquor Handbook 1999,* 135.

In all cases, pricing was uniform and dictated by the state, leaving very little room for promoting brands. In most control states, retail prices were much higher than those in "open" neighbor states, but there were a few notable exceptions, such as New Hampshire and Pennsylvania. Temporary discounts and displays were allowed but highly regulated (and each state has its own set of rules) and needed to go through a lengthy approval process with the local liquor board. Shelf positioning was not negotiable. Another limitation in control states was the lack of convenience: Many had an insufficient number of stores, often with poor locations and limited operating hours.

Off-premise retailers were divided into food, drug, and liquor stores. Food stores included groceries, delis, and larger wholesale clubs. Drugstores such as Walgreens comprised the drug category. Liquor stores were further divided into the independent and control-state-owned liquor stores. Cuvelier estimated that the breakdown was 35%, 20%, and 45% for food, drug, and liquor stores, respectively. "The big chains, across all categories, were harder to penetrate, since they required high margins and heavy marketing support and established market share," he explained. "These bigger outlets relied on strong consumer pull for top brands."

For vodka, independent retailers were responsible for significant volume sales. And they could give the brand strong and sustained support because they generated higher margins on SVEDKA than high-volume established brands while offering a very competitive price. The pricing of SVEDKA, Cuvelier thought, would be attractive to them—which translated into eye-level shelf positioning, floor displays, and spontaneous retailers' recommendations. By prominently displaying SVEDKA alongside key competitors, store owners could give the brand invaluable credibility. And so SVEDKA planned to concentrate sales efforts on these midmarket retail outlets. In particular, Cuvelier intended to focus on landing the family-owned operations, considered midtier stores in terms of traffic and business, and devote very little effort to the chain stores such as large grocery and drug chains that also sold liquor in noncontrol states.

The distribution strategy for SVEDKA required a network of wholesalers and brokers. Cuvelier thought it would be difficult to gain a foothold among large wholesalers in the biggest states, so he looked for what he called "challenger" distributors where he could get more attention and support from management and sales. These operated primarily in open states. (See **Exhibit 5** for retail sales of vodka in the top 25 states by retail sales in 1998.) Robust collateral pieces explaining the benefits of the product, brand, and company were given to all retailers as education materials.

Cuvelier believed that, given his limited budget, launching SVEDKA in the midmarket off-premise locations was the most effective strategy. He instructed his sales force to secure distribution in liquor stores only. But he still harbored doubts about which particular states he should select and the order in which they would receive SVEDKA shipments.

The Brand

The first association consumers would have with the product was its name. Cuvelier had searched for a word that evoked the vodka's Swedish heritage. During his many trips to Sweden, the word *Svensk* ("Swedish") caught his attention; it appeared everywhere. He combined it with the word "vodka" to come up with an easier-to-pronounce version: SVEDKA. Although focus groups and the packaging agency didn't confirm the wisdom of his choice, Cuvelier stayed with his intuition. (**Exhibit 7** shows the SVEDKA bottle with its original logo, which has since been updated.)

The name was fitting for the product's positioning. Cuvelier envisioned SVEDKA as a challenger brand, with a personality like JetBlue in the airline industry or Target in fashion: an inexpensive, chic alternative. It was a fun option that challenged the status quo in a category that was taking itself too seriously. SVEDKA empowered the consumer with a different choice where there wasn't much discrepancy among the products in its category. "The category is locked in sameness," Cuvelier said. "Each brand relies on a stated marketing recipe of bottle shot plus product benefit plus cocktail recipe plus historical reference.[18]

The Campaign

Cuvelier estimated he had about $350,000 to spend in his first year on marketing SVEDKA (not including promotions to wholesalers and retailers, which could include the discount levels, support materials, sales force incentives, and in-store promotions). He allocated this budget among media, point of sale (POS), trade shows, creative, and sampling.

Until distribution reached key markets, Cuvelier did not use traditional advertising. Generally, brands were promoted in print (with magazines as the dominant medium), outdoor, broadcast, and electronic media at an increase of 14% over the $256 million spent in 1997.[19] (Refer to **Exhibit 8** for the total advertising expenditure in 1997 and 1998.) Cuvelier wanted SVEDKA to achieve distribution, brand awareness, and word of mouth before he launched a national campaign. He was left to reassess the best use of his dollars across the following marketing methods.

Trade press and PR

Cuvelier viewed trade relationships as the first step in communicating about his brand. There were a small but influential group of trade magazines and writers he needed to acquaint with SVEDKA. He bought a few full-page trade ads and entered SVEDKA in vodka contests to drum up press. He succeeded with the *Wine Enthusiast* 93 rating. Such high marks were in line with the more expensive Grey Goose (which received a 94) and Ketel One (93) and higher than the ratings for Stolichnaya (91), Skyy (90), Belvedere (89), and Absolut (90).[20] The favorable results validated the brand in the eyes of the wholesalers. Their excitement about SVEDKA would determine how quickly it was embraced by the largest, bottom portion, the core consumer. All media outreach was limited to the trade outlets. SVEDKA used its high-profile reviews to fuel favorable trade press articles. But additional public relations efforts toward larger publications were not scheduled for the launch.

Point of sale

Brand visibility would be at the store level through POS materials. Because of the emphasis on an off-premise distribution strategy, Cuvelier allocated marketing dollars toward enhancing the in-store experience (midtier liquor stores). POS and store signage (shelf, display, and window materials) helped bring the brand to life at the point of decision making and purchasing. The *Wine Enthusiast* ranking was displayed on POS pieces to provide the unknown product with credibility.

Trade shows

SVEDKA planned to sponsor booths at top industry trade shows. Attendees at these shows included wholesalers and retailers, as well as the media and competition. Although trade shows were costly and time-

[18] SVEDKA corporate presentation.
[19] *Adams Liquor Handbook 1999,* 227.
[20] *Wine Enthusiast* ratings, 1999, 2004, and 2007.

consuming, Cuvelier believed that having a presence at industry events would develop brand recognition as well as provide continuing insight into industry trends.

Creative

The collateral materials that supported the SVEDKA booth at trade shows, in addition to the POS materials and trade press kits, fell under the creative investment line item. Cuvelier wanted all branding elements to have a cohesive look and feel for both internal and external audiences. The same images appeared as limited ads in trade magazines such as *Beverage Industry News*.

Sampling

And finally, when the product was to be introduced in a new store, SVEDKA intended to host sampling events. SVEDKA wanted to put its own twist on the customer-engagement tactic by designing customized, branded barware test tubes. Cuvelier was certain that the ROI on these 1,000 to 1,500 sampling events per year (two to three hours per event with a small staff and collateral materials) was enormous. SVEDKA had only one shot at the launch campaign, and Cuvelier was confident in his tactics. But he did find himself reexamining his budget in the final days before his product's debut.

Exhibit 1

SVEDKA Vodka (A)

Projections: Vodka versus Total Distilled Spirits
(in thousands of 9 L cases)

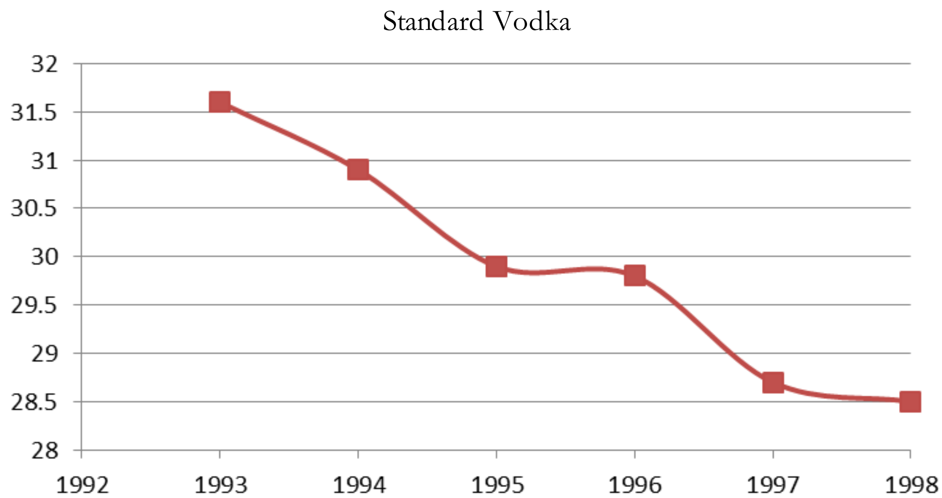
	Vodka		Total Distilled Spirits	
Year	**Cases**	**ACGR***	**Cases**	**ACGR**
1975	31,898	-.-%	179,731	-.-%
1980	36,411	2.7	190,903	1.2
1985	35,681	–0.4	173,508	–1.9
1986	34,717	–2.7	164,531	–5.2
1987	33,626	–3.1	162,024	–1.5
1988	34,712	3.2	159,008	–1.9
1989	35,054	1.0	155,865	–2.0
1990	35,362	0.9	159,190	2.1
1991	33,397	–5.6	147,026	–7.6
1992	32,964	–1.3	148,015	0.7
1993	32,441	–1.6	144,162	–2.6
1994	31,910	–1.6	139,996	–2.9
1995	32,175	0.8	137,330	–1.9
1996	33,002	2.6	138,814	1.1
1997	32,912	–0.3	138,740	–0.1
1998	34,088	3.6	140,568	1.3
1999 projected versus 1998	35,000	2.7	141,905	1.0
2003 projected versus 1998	35,500	0.8	143,240	0.4

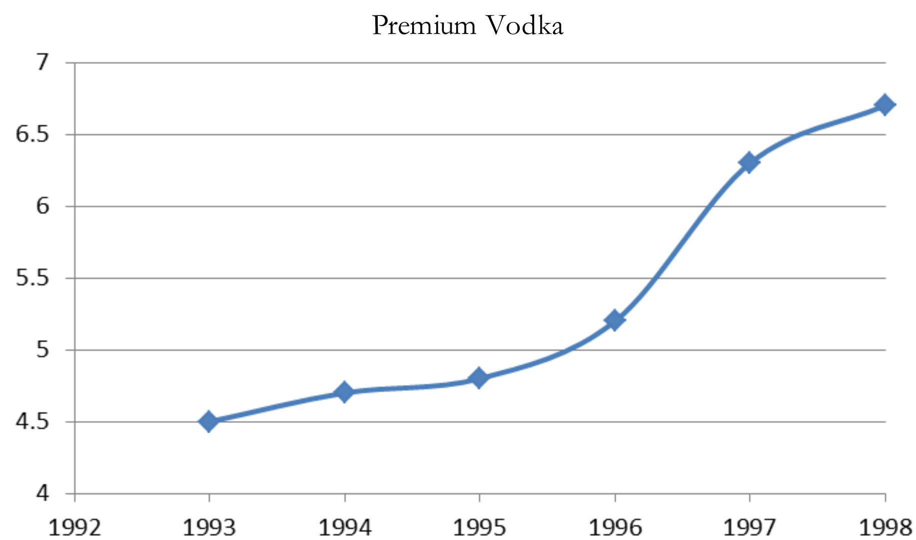
*Annual compound growth rate.

Data source: *Adams Liquor Handbook 1999*.

Exhibit 1 (continued)

Vodka Sales, 1993 to 1998 (in millions of 9 L cases)





Source: SVEDKA sales presentation, 2001.

Exhibit 2

SVEDKA Vodka (A)

New Distilled Spirits Introductions by Category, 1996–98

	Number of Introductions				Share of Total		
Category	1996	1997	1998	Category	1996	1997	1998
U.S. whiskey	10	14	19	U.S. whiskey	3.9%	6.1%	5.1%
Canadian	7	1	5	Canadian	2.7	0.4	1.3
Scotch	39	18	42	Scotch	15.3	7.8	11.3
Irish	2	2	4	Irish	0.8	0.9	1.1
Total whiskey	**58**	**35**	**70**	**Total whiskey**	**22.7%**	**15.2%**	**18.9%**
Gin	11	5	10	Gin	4.3	2.2	2.7
Vodka	37	24	23	Vodka	14.5	10.4	6.2
Rum	31	26	27	Rum	12.2	11.3	7.3
Tequila	19	24	46	Tequila	7.5	10.4	12.4
Brandy and cognac	29	44	104	Brandy and cognac	11.4	19.1	28.0
Cordials and liqueurs	44	50	72	Cordials and liqueurs	17.3	21.7	19.4
Prepared cocktails	26	20	18	Prepared cocktails	10.2	8.7	4.9
Neutral spirits	- -	2	1	Neutral spirits	-.-	0.9	0.3
Total nonwhiskey	**197**	**195**	**301**	**Total nonwhiskey**	**77.3%**	**84.8%**	**81.1%**
Total	**255**	**230**	**371**	**Total**	**100.0%**	**100.0%**	**100.0%**

Data source: Adams Liquor Handbook 1999, 5.

Exhibit 3

SVEDKA Vodka (A)

Supplier Vodka Case Prices

Price Ranges	**Percentage**
Under $34.99	16.5
$35.00 to $39.99	21.4
$40.00 to $49.99	18.8
$50.00 to $59.99	22.1
$60.00 to $99.99	2.8
$100.00 to $119.99	18.3
Total	100.0

Data source: Adams Liquor Handbook 1999, 135.

Exhibit 4

SVEDKA Vodka (A)

Consumers of Distilled Spirits by Category and Age Group
(in percent)

	Age Groups						Total
Category	**21–24**	**25–34**	**35–44**	**45–54**	**55–64**	**65+**	**Adults**
Distilled spirits	62.7	60.6	55.2	53.1	44.4	35.2	51.7
Bourbon	15.2	13.6	12.8	12.3	12.6	9.5	12.5
Blend/rye	3.7	6.3	6.0	6.6	7.3	5.9	6.2
Canadian	6.9	10.0	11.6	11.3	13.3	9.1	10.7
Scotch	6.7	8.3	9.0	12.9	11.4	8.8	9.7
Irish	3.5	3.0	3.7	4.5	3.0	2.3	3.3
Gin	16.5	15.3	15.0	16.4	13.7	10.4	14.5
Vodka	30.4	29.6	25.5	24.5	21.8	15.4	24.3
Rum	34.4	28.2	26.0	23.1	15.8	7.9	22.1
Tequila	26.7	24.9	20.1	17.9	9.5	5.1	17.2
Brandy and cognac	4.1	7.3	8.3	11.0	8.8	7.7	8.2
Cordials and liqueurs	27.3	21.6	21.6	21.9	19.0	11.6	20.0
Adult population (in millions)	**12.3**	**38.9**	**43.1**	**34.4**	**22.1**	**31.9**	**182.7**

Note: Includes consumers age 21 and older only.

Data sources: Simmons Market Research Bureau, *Spring 1998 Study of Media and Markets*; *Adams Liquor Handbook 1999,* 291.

Exhibit 5

SVEDKA Vodka (A)

Retail Sales for Vodka in Top 25 States, 1998
($$ in millions)

Rank	State	Sales	Control or Open	Percent Share of All Distilled Spirits
1	California	$738	Open	10.40
2	Florida	$517	Open	6.50
3	New York	$468	Open	7.40
4	Illinois	$341	Open	5.00
5	Texas	$333	Open	5.80
6	New Jersey	$317	Open	3.90
7	Pennsylvania	$307	Control	3.70
8	Michigan	$296	Control	3.70
9	Ohio	$221	Control	3.50
10	Georgia	$203	Open	2.80
11	Washington	$198	Control	2.50
12	Wisconsin	$190	Open	2.80
13	Connecticut	$179	Open	1.90
14	Massachusetts	$177	Open	3.20
15	South Carolina	$149	Open	1.70
16	Arizona	$147	Open	1.80
17	North Carolina	$146	Control	2.00
18	Minnesota	$144	Open	2.10
19	Maryland	$140	Open	2.00
20	Colorado	$139	Open	1.90
21	Virginia	$133	Control	2.00
22	Indiana	$127	Open	1.90
23	Tennessee	$117	Open	1.40
24	Missouri	$113	Open	1.80
25	Louisiana	$102	Open	1.70
	Top 25	**$5,942**		**84.00**
	Bottom 25	**$1,280**		**16.50**
	Total United States	**$7,222**		**21.20**

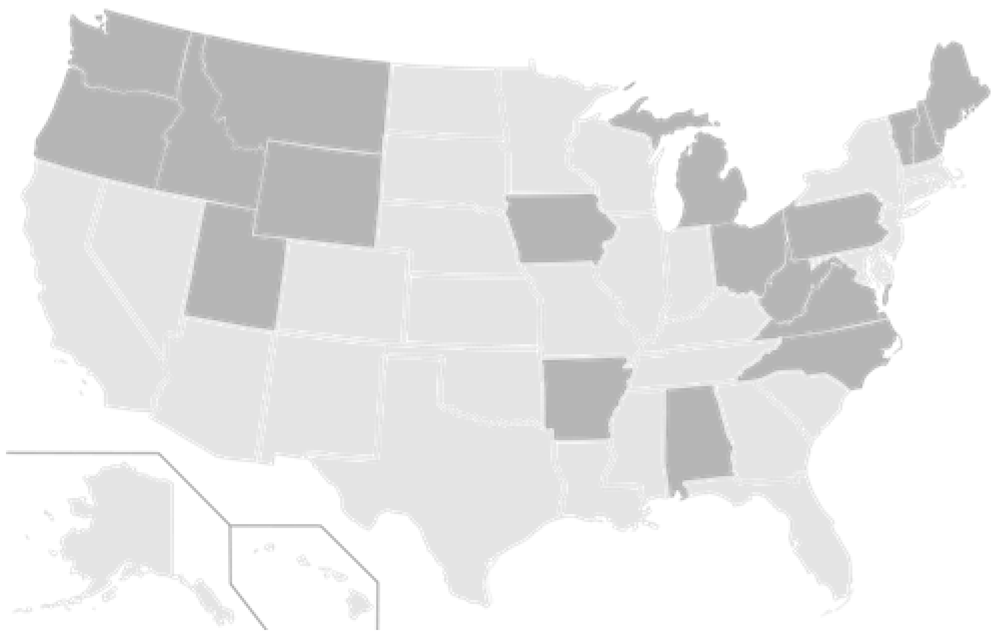
	Control	Open
Top 25	6	19
Total United States	18	32
Top 25 vodka sales, in millions	$1,301	$4,641
Top 25 percent share	22	78

Data source: Adams Liquor Handbook 1999, 34.

Exhibit 6

SVEDKA Vodka (A)

Map of Control (Dark) and Open (Light) States



Data source: "US States by Alcohol Control," posted to public domain under Creative Commons (CC BY-SA 3.0) by "Demi," November 8, 2006, http://en.wikipedia.org/wiki/File:US_States_by_alcohol_control.svg (accessed May 22, 2009).

Exhibit 7

SVEDKA Vodka (A)

SVEDKA Bottle with Original Logo

Source: SVEKDA.

Exhibit 8

SVEDKA Vodka (A)

Total Advertising Expenditures for Vodka, 1997–98
($$ in thousands)

	1997					1998				
Brand	**Mag.**	**News.**	**Outdoor**	**B'cast**	**Total**	**Mag.**	**News.**	**Outdoor**	**B'cast**	**Total**
Absolut	$27,013.9	$201.7	$515.7	—	$27,731.3	$27,617.0	$308.2	$1,420.4	$161.9	$29,507.5
Smirnoff	12,363.3	80.0	866.3	—	13,309.6	14,558.1	391.3	856.2	18.2	15,822.8
Finlandia	2,412.2	0.4	1.8	—	2,414.4	8,156.4	90.2	575.6	325.9	9,148.1
Stolichnaya	7,662.9	182.4	—	—	7,845.3	6,799.6	173.0	—	—	6,972.6
Skyy	3,816.8	—	—	—	3,816.8	3,259.7	—	224.1	—	3,483.8
Belvedere	116.2	—	—	—	116.2	518.1	863.3	—	—	1,381.4
Grey Goose	—	—	—	—	—	—	547.4	—	—	547.4
Chopin	60.3	—	—	—	69.3	274.9	242.1	—	—	517.0
Argent	—	—	—	—	—	58.2	236.2	—	—	294.4
Taaka	—	—	237.0	—	237.0	—	—	286.1	—	286.1
Georgi	—	156.7	—	—	156.7	—	177.3	—	—	177.3
Fleischmann's Vodka	—	—	137.5	—	137.5	—	—	167.4	—	167.4
Gordon's Vodka	2,471.8	—	—	—	2,471.8	105.8	—	—	—	105.8
Stolichnaya Cristall	—	—	—	—	—	82.1	14.8	—	—	96.9
Rain Vodka	—	—	—	—	—	30.0	—	—	—	30.0
Iceberg	—	35.6	—	—	35.6	27.3	—	—	—	27.3
McCormick Vodka	—	—	107.5	—	107.5	—	—	7.9	—	7.9
Tanqueray Sterling	2,007.8	—	299.1	—	2,306.9	—	—	—	—	—
Wyborowa	—	115.0	—	—	115.0	—	—	—	—	—
Kremlyovskaya	30.9	—	—	—	30.9	—	—	—	—	—
Total expenditure	**$57,965.1**	**$771.8**	**$2,164.9**	**—**	**$60,901.8**	**$61,487.2**	**$3,043.8**	**$3,537.7**	**$506.0**	**$68,574.7**

Data sources: Competitive Media; *Adams Liquor Handbook 1999,* 136.

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SVEDKA Vodka (B)

SVEDKA had sold 25,000 cases by the end of 1998. Initial volume sales results, press coverage, and sales feedback validated Guillaume Cuvelier's assessment of SVEDKA's market opportunity. Retailers and consumers responded to the product's value and appealing price. SVEDKA had identified and fulfilled a need for a high-quality imported vodka at a midlevel price point.

By 1999, SVEDKA was available in 15 of the states in its market. The number increased to 44 within three years, and, by 2003, the brand had achieved national distribution. Cuvelier told *BIN* magazine in December 2003: "As a marketer, it is most exciting for me to see the product so well displayed in stores. A good product, well marketed, intrinsically translates to high volume."[1]

The Results

In 2006, SVEDKA reached an important industry benchmark, selling one million cases. That same year, vodka was the largest growth category of any major international spirits sector.[2] According to a 2008 Information Resources, Inc., report, SVEDKA ranked fifth in the combined liquor, food, and drug categories for imported vodka (**Table 1**).[3]

By 2007, SVEDKA had become the fastest-growing imported vodka in the United States. In March 2007, Cuvelier sold SVEDKA for $384 million to Constellation Brands, Inc. The move took place when consolidation in the industry was rife with such deals as Bacardi's acquisition of Grey Goose in 2004.[4] In its first quarter as part of a publicly traded company, SVEDKA continued its growth trajectory with double-digit gains and continued to enjoy rapid growth in 2009.

[1] "High Spirits: The Rise of SVEDKA," *BIN,* December 2003.
[2] "Vodka Meets with Growing Global Appeal," *International Wine and Spirit Record*, September 2007, 6.
[3] Information Resources, Inc., "52-Week Report Ending March 23, 2008, for U.S. Food, Drug, and Liquor, Vodka." Drugstores came last because it was much harder to gain distribution in that category. Even at this stage, SVEDKA was still pushing to get full distribution in this channel; that was why SVEDKA's ranking was not so high.
[4] "Bacardi to Buy Grey Goose Vodka," *Associated Press*, June 21, 2004.

Table 1. Premium imported vodka for the 52-week period ending March 23, 2008.

Rank	Brand	Sales	% Change $ versus YAG	Share of Category	9 L Case Volume	9 L Case Share
1	Absolut	$127,546,278	8.50%	11.40%	604,592	6.00%
2	Grey Goose	$ 78,157,569	16.70%	7.00%	234,779	2.30%
3	Ketel One	$ 60,311,956	1.60%	5.40%	259,929	2.60%
4	Stolichnaya	$ 54,773,915	7.60%	4.90%	302,678	3.00%
5	SVEDKA	$ 30,422,281	45.10%	2.70%	256,610	2.50%
6	Three Olives	$ 12,571,144	38.80%	1.10%	65,167	0.60%
7	Belvedere	$ 11,773,674	1.80%	1.00%	34,828	0.30%
8	Finlandia	$ 7,396,797	–12.40%	0.70%	45,710	0.50%

Notes: These data are useful for market shares but not for total volume or dollars sold; YAG = year ago.

Data source: Information Resources, Inc.

The Product

Cuvelier believed that flavored vodka was a necessary step for the brand to be viewed as a major force in the category, even if the standard vodka contributed to the majority of sales. After focus group testing, SVEDKA extended its brand, offering citron, clementine, raspberry, and vanilla flavors in 2003 and 2004. In the summer of 2009, a cherry flavor was added. These flavored versions were 37.5% alcohol, or 75 proof, whereas standard vodka was 40% alcohol, or 80 proof. All flavor varieties were priced the same as the regular vodka. Around the same time, the 200 mL and 375 mL sizes were introduced. And in 2008, SVEDKA tweaked the bottle design. (**Exhibit 1** depicts the newer packaging and various flavors.)

SVEDKA continued to receive favorable product reviews, which added to the credibility it had established with the high *Wine Enthusiast* marks. For example, *F. Paul Pacult's Spirit Journal* gave SVEDKA four stars, deeming it "an outstanding value."[5] The brand won numerous awards, such as the gold medal at both the 2002 International Wine and Spirit Competition and the 2003 World Spirit Competition.

Distribution

Cuvelier attributed much of the brand's success to his focus on distribution in the early years. "SVEDKA has essentially emerged from a core independent retail network," he said. "They have made the brand what it is today."[6] After a few years of making inroads in the off-premise channel, it became clear that SVEDKA needed a presence in the bars and restaurants as well. By 2004, Cuvelier wanted his team to focus on trendy bars where the opinion leaders decided on the next hip brand. Given SVEDKA's limited resources, this initiative targeted select accounts in key urban markets such as New York and Los Angeles, where the brand was sampled, promoted, and featured consistently.

Each year, more high-profile restaurants and clubs were added, including Starwood Hotels and Resorts Worldwide, including its trendy W luxury hotel chain, and Ruth's Chris Steak House. These were important wins for the brand. A bar's willingness to carry the product validated that SVEDKA had generated enough consumer knowledge and pull.

[5] F. Paul Pacult, "SVEDKA Vodka," *F. Paul Pacult's Spirit Journal,* March 2000.

[6] Case writer interview with Guillaume Cuvelier, October 13, 2008; unless otherwise indicated, all subsequent attributions derive from this interview.

The Brand

When SVEDKA hit the shelves, Cuvelier wanted to ensure that the product created an emotional connection beyond the vodka itself, a phenomenon similar to Absolut's. During a SVEDKA corporate presentation, he said: "SVEDKA had to mean more than a product to its core audience. It was an experience, a lifestyle, and above all a fun brand."

Unlike other brands, which looked to the past for justification, Cuvelier wanted SVEDKA to suggest the future, the language of its core target. (See **Exhibit 8** for SVEDKA's assessment of competitors' marketing campaigns from 2007–08.) Absolut marketed its bottle silhouette in its advertisements, and other competitors such as Stoli used the heritage angle. Cuvelier believed the "tradition" message didn't make much sense for the category. Vodka, unlike other spirits such as Cognac, was not aged, so the tradition would not play an important part in the purchaser's decision.

SVEDKA's positioning as a high-quality imported vodka at an affordable price, to be enjoyed while having fun with friends, focused on the end benefits of vodka rather than telling a story about the vodka itself. SVEDKA promoted itself as both a rational and aspirational product, and Cuvelier wanted his vodka to be equated with festive social occasions during which consumers would enjoy it.

The first step in communicating the brand was explaining it to the internal team. The sales team was trained on the product's core promises, brand attributes, and competitive positioning. Words such as "freedom," "fresh thinking," and "flirtatious" were used in presentations to describe the brand's essence. The SVEDKA consumer was described internally as a sophisticated, "casual-cool," iconoclastic, and authentic person. Above all, the brand strategy—a light-on-the-wallet yet high-quality vodka—was reinforced.[7]

Trade Campaign (1998–2002)

In keeping with the brand's origin, the first campaign featured two young, Nordic-looking blond women, "the SVEDKA sisters," who urged consumers to "try something Swedish tonight." (See **Exhibits 2** and **3** for examples of sales collateral and a tent card from this campaign.) The first target audience was the trade, specifically the wholesalers' salespeople, most of whom were middle-age males working on commission. The goal was not only to get their attention but also to show that the brand was spending money to promote the launch in bars and stores. Given the limited budget, the campaign had to feel bigger than it really was; hence a provocative message supported with numerous point-of-sale materials. In 2000, the marketing budget of less than $350,000 covered the posters, logo roll banners, table tents, T-shirts, case cards, and shelf talkers. Each year thereafter, additional funds were allocated to support more media, public relations, and promotions.

In 2001, Cuvelier began working with a small marketing firm to execute promotions, bar nights, and sampling events. The marketing budget had more than tripled from 2000; since 1998, resources had been allocated to selling and developing the distribution network. SVEDKA models gave free Swedish massages to drum up interest in trying the product; that way, the consumer could actually experience the provocative and fun nature of SVEDKA. A limited radio buy supported the efforts in targeted local markets; however, Cuvelier spent most of the $500,000 budget to run 15 bar nights per month in three select markets.[8] The 2002

[7] SVEDKA corporate presentation, April 9, 2001.
[8] SVEDKA corporate presentation.

media spend was more than 100% above the previous year's. The entire SVEDKA marketing budget was up more than 30%.

National Campaign 1: PR (2003)

As sales grew, Cuvelier faced a common marketing dilemma: how to bring his brand mainstream without alienating his initial customer base. He wanted to maintain SVEDKA's brand equity and integrity but also have it known to the masses. "We think we can remain provocative and fun but still speak to a broader group," Cuvelier told the *Wall Street Journal* in September 2005.[9] Image-conscious 21- to 30-year-old consumers remained the core audience. The answer would be to speak loud and clear in a different way. In the fall of 2003, Cuvelier was ready to take risks, invest more dollars in marketing, and introduce the brand's first national campaign. The objective was to get noticed by opinion leaders. SVEDKA relied on making noise with its ads to put itself on the map.

Marina Hahn was brought in as marketing director and applied her years of experience in building brands at Pepsi and Sony to managing SVEDKA's advertising campaign. Themed "Adult Entertainment," the ads featured such images as a nude, goose-bumped woman holding a shot glass between her breasts as someone splashes vodka into it and down her torso.[10] SVEDKA won *Impact* magazine's 2003 Hot Brand Award. SVEDKA became a brand regularly mentioned in *People*, *US Weekly*, and the *New York Post* as the vodka of choice among the young celebrity crowd.

National Campaign 2: Advertising (2005)

To many, SVEDKA was known for its 2005 advertising campaign, created by the New York-based agency Amalgamated. Building on the PR campaign, marketing wanted to push things even further. SVEDKA_Grl was introduced as the futuristic and provocative mascot (**Exhibit 4**). Her sexy image appeared on the website and in advertising and buzz marketing pieces. The brand rallying cry "Voted #1 Vodka in 2033" was used in the ads to offer social commentary on hot topics of the day. SVEDKA_Grl set her own rules and delivered tongue-in-cheek messages on current events such as stem cell research and smoking bans. She appeared on billboards, bus shelters, and wallscapes in key markets such as New York, Chicago, San Francisco, and Boston.

Once again, the press responded. This time, industry associations weighed in as well. SVEDKA's ads twice drew censure from the Distilled Spirits Council (DISCUS) for using sex to sell alcohol. Although the industry's self-regulating body didn't impose a fine or require that ads be pulled, all major liquor companies that were DISCUS members voluntarily pulled or altered censured ads. SVEDKA was not a DISCUS member and did not retreat from its ad strategy. "We're not talking about Pampers here," Hahn told the *Wall Street Journal*. "We're talking about vodka."[11] SVEDKA's growth rates accelerated from 35% to 40% to 60%. Perhaps just as important as the sales results, the campaign brought life and awareness to the brand. SVEDKA had a clear personality that consumers recognized across all the marketing vehicles.

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[9] Deborah Ball, "SVEDKA Hopes to Broaden Its Edgy Appeal," *Wall Street Journal,* September 7, 2005.
[10] Ken Magill, "SVEDKA Pours It On," *New York Sun*, January 5, 2004.
[11] Ball.

Competition

While SVEDKA was growing, so was the number of vodkas in the market. In 2003–04, other brands began to follow SVEDKA's strategy, updating their angles to reflect the hip, cool, and social target consumer. "This was an indicator that we had been successful," Cuvelier said. In 2005, 761 different vodka stock-keeping units (SKUs) were for sale, an increase of almost 56% from 2000, according to DISCUS.[12] The new additions reflected the trends of the times. Organic vodkas and energy vodkas entered the market in 2007.[13] Celebrity endorsements emerged as an important seal of approval: In 2007, Sean "Diddy" Combs agreed to become the spokesperson for Cîroc, which had been introduced in 2003.

The market's dynamics were changing. (Refer to **Exhibit 5** for sales figures.) Industry data pointed to the fact that Absolut was slowing down, while Grey Goose was gaining ground.[14] Trying to protect its share of top-shelf sales, in 2004, Absolut introduced Level.[15] One thing that was increasing for the majority of brands (2005–07) was ad spend. The top three competitors outspent SVEDKA by as much as 7:1 (**Exhibits 6** and **7**).

Future

When he sold SVEDKA to Constellation Brands in 2007, Cuvelier retired from the world of vodka to pursue his next entrepreneurial venture. Without its founder, SVEDKA faced its next set of challenges—including how to be cutting-edge—now that it was owned by a conglomerate, remain relevant instead of becoming a fad of the past, and expand its reach in new markets.

At the end of 2008, the brand marked its 10-year anniversary, and the United States entered a recession. In January 2009, SVEDKA was highlighted as a midpremium spirits brand that was outperforming the marketplace. As of April 2009, SVEDKA was the number-one growth brand within the top 100 premium spirits worldwide.[16] The brand had become the third-largest imported vodka in the United States, behind only Absolut and Grey Goose.[17]

[12] Noah Rothbaum, The Business of Spirits: How Savvy Marketers, Innovative Distillers, and Entrepreneurs Changed How We Drink (New York: Kaplan Publishing, 2007), 43.
[13] Eric Felten, "Make Mine a 020001," Wall Street Journal, September 1, 2007.
[14] "Growth in Vodka," Impact, 2006.
[15] Theresa Howard, "Absolut Puts a New Premium on Vodka," USA Today, March 30, 2004.
[16] "Beverage Information Group, Leading Brands of Vodka, 2004–2008," Handbook Advance 2009.
[17] Drinks International, "Millionaires Club Supplement," July 2009.

Exhibit 1

SVEDKA Vodka (B)

Flavor Extensions and New Packaging (2009)

Source: All exhibits, unless otherwise noted, provided by SVEDKA.

Exhibit 2

SVEDKA Vodka (B)

Sales Collateral (2004)

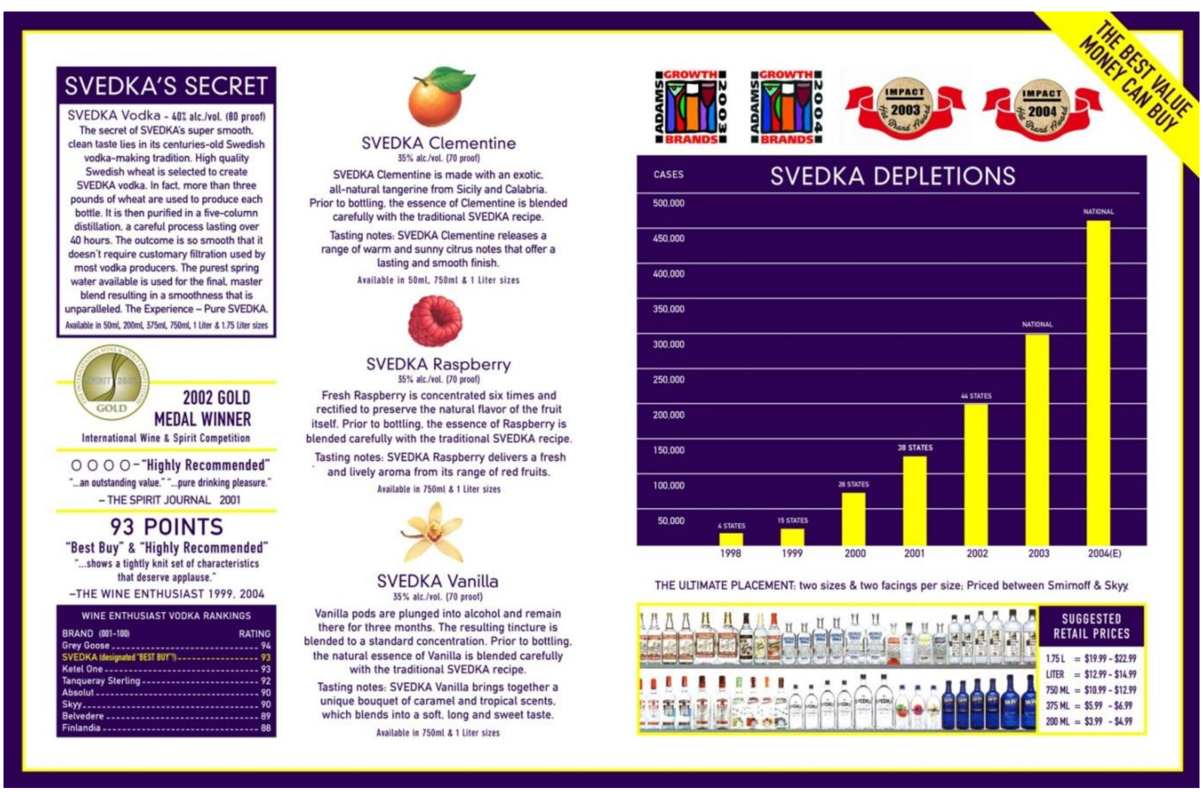

Exhibit 3

SVEDKA Vodka (B)

Trade Campaign (2000–02)

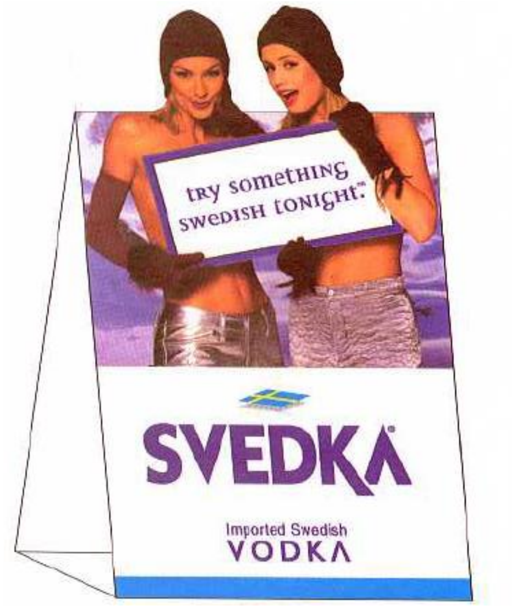

Exhibit 4

SVEDKA VODKA (B)

Print Advertisement (2008)

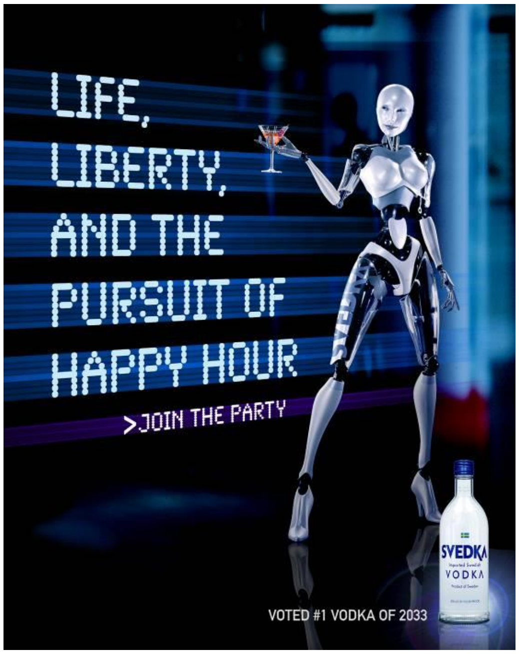

Exhibit 5

SVEDKA Vodka (B)

Leading Brands of Vodka, 2002–07
(in thousands of 9 L cases)

Brand	Origin	Supplier	2002	2003	2004	2005	2006	2007
Absolut	Sweden	Absolut Spirits Co.	4,475	4,488	4,640	4,636	4,847	5,013
Grey Goose	France	Bacardi USA	1,150	1,400	1,650	2,075	2,660	3,325
Stolichnaya	Russia	Pernod Ricard USA	1,640	1,855	1,935	1,985	2,090	2,185
Ketel One	Netherlands	Nolet Spirits USA	1,054	1,243	1,438	1,593	1,753	1,858
SVEDKA	Sweden	Constellation Spirits Marque One	200	306	448	640	1,023	1,526
Three Olives	United Kingdom	Proximo Spirits	85	175	350	475	630	850
Belvedere Vodka	Poland	Moët Hennessy USA	306	339	369	365	381	410
Finlandia	Finland	Brown-Forman Beverages	319	327	357	375	381	362

Data source: Adams Liquor Handbook 2003, 145.

Exhibit 6

SVEDKA Vodka (B)

Advertising Spend, 2005–07
(dollars in thousands)

Brand	2005 Dollars	2006 Dollars	2007 Dollars
Absolut	$18,651.6	$26,000.5	$24,836.4
Grey Goose	26,931.2	18,878.6	21,809.6
Ketel One	17,892.4	22,608.5	24,171.0
Imperia	0.0	1,140.3	3,269.8
Level	9,711.0	8,032.6	4,987.4
Russian Standard	11.3	0.0	4,767.0
SKYY	12,028.9	11,801.0	14,919.0
Smirnoff	10,995.2	8,972.2	11,357.8
Stolichnaya	7,272.3	5,532.1	11,287.2
SVEDKA	730.9	1,614.6	4,209.6
Three Olives	4,668.7	7,106.6	11,385.5
Total	**$108,893.5**	**$111,687.0**	**$137,000.3**

Data sources: SVEDKA; TNS Media Intelligence Report.

Exhibit 7

SVEDKA Vodka (B)

Media Spend
(dollars in thousands)

Brand	2006 Media Spend	Depletions	Media Investment per Case Depletion	Spend Ratio versus SVEDKA
Absolut	$26,068	4,900	$ 5.32	3 to 1
Grey Goose	$19,539	2,660	$ 7.35	5 to 1
Ketel One	$22,609	1,755	$12.88	8 to 1
SKYY	$12,032	2,275	$ 5.29	3 to 1
Smirnoff	$19,630	8,865	$ 2.21	2 to 1
Stolichnaya	$ 7,354	2,100	$ 3.50	2 to 1
SVEDKA	**$ 1,600**	**1,037**	**$ 1.54**	
Three Olives	$ 7,107	630	$11.28	7 to 1

Data sources: SVEDKA; CMR Strategy.

Exhibit 8

SVEDKA Vodka (B)

Competitive Review (2007–08)

BRAND	POSITIONING	AD STRATEGY
Absolut	Ideal world is Absolut world	Flavor and special-release products Regain solidarity in category it defined Product placements (*Sex and the City*)
Belvedere	Luxury	New in October 2007 Happenstance led to product placements
Grey Goose	Elitist brand Best-tasting message	Lifestyle-focused on finer things in life 35–45 audience
Ketel One	Club of drinkers	Clever copy "Thank you for your support" message Word of mouth spread the brand
SKYY	Ultra-hip	Lifestyle-focused
Smirnoff	Mixability of flavors Benefit oriented Smirnoff Ice advantage	*New York Times* taste test Super Me Younger male target audience
Stolichnaya	Authentic Russian heritage Aspirational	First name in flavor Younger male target audience

Data sources: Distilled Spirits Council of the United States, December 2007; *TNS Media Intelligence Report, 2008*.

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SVEDKA Vodka (C): Marketing Mix in the Vodka Industry

Associated with sophistication ever since James Bond first ordered a vodka martini "shaken, not stirred," vodka enjoyed tremendous success over the decades leading up to SVEDKA's debut. The enthusiasm for vodka by the women of the hit HBO series *Sex and the City* provided renewed energy for vodka in early 2000, just as the more-than-40-year bump Bond had provided was losing its luster. In 2007, Smirnoff was the highest-selling spirit brand worldwide (25.7 million cases) and in the United States (9 million cases). U.S. vodka sales topped $7 billion in 2007, and two spots in the top five spirit brands worldwide belonged to vodka brands Smirnoff and Absolut.[1]

Product

Between 2000 and 2007, the number of vodka brands increased from 14 to 26. Flavors and packaging were the more popular product variations introduced. Absolut was the first to introduce flavored vodka in 1986, using three types of peppers. The company called it Absolut Peppar (peh-PAR) and proclaimed it to be perfect for a Bloody Mary. Smirnoff and Absolut introduced the most flavors, and by 2007, Smirnoff's product line included 20 different flavors while Absolut had more than 10. Innovative packaging evolved, starting with Absolut's recognizable shape, inspired by a vintage Swedish apothecary bottle. By 2011, brands such as Vox and Cîroc were bottled in elegant frosted glass.

Price

In 1997, Grey Goose invented the super-premium category, marketing a 750 mL bottle of vodka priced above $30. Vodka retail prices varied across states because of taxes and the regulation of distributors. The wholesale price of a 9 L case of vodka was above $200 for such super-premium brands as Chopin, Belvedere, Grey Goose, and Level, whereas the prices of some value brands such as Aristocrat, McCormick, Barton, and Crystal Palace were below $35 per 9 L case.[2]

Advertising

By 2007, the industry had spent more than $200 million on advertising through various channels including outdoor, magazine, newspaper, and television.

[1] Drinks International, "Millionaires Club Supplement," July 2009.
[2] *Adams Liquor Handbook, 2007.*

TV advertising of alcoholic drinks had been controversial; indeed, for 48 years, liquor producers had chosen not to air commercials. In 1996, Seagram's broke that trend with network spots promoting Crown Royal and Lime Twisted Gin. In spite of the public outcry that arose, other liquor brands slowly started testing cable TV spots. Eventually, cable television came to be seen as the most suitable venue for liquor advertising.

The print ads for vodka were very sophisticated. In 1980, Absolut began featuring its bottle's distinct silhouette, a practice it continued for more than two decades. Its innovative campaign prompted an account rep at TBWA, Absolut's ad agency, to write a book in 1996 about its print campaign.

Grey Goose won the Beverage Tasting Institute award for the best-tasting vodka in 1998 and used the title in a series of successful print campaigns in the *Wall Street Journal* and other high-end publications. In the same year, *Sex and the City* characters started asking for a "Grey Goose cosmopolitan," which extended the brand's recognition and super-premium image.

Distribution

In 1919, a constitutional amendment banned the manufacture, sale, and transporting of alcohol in the United States. With the repeal of Prohibition in 1933, U.S. alcohol distribution was highly regulated via a three-tier system that restricted producers from direct distribution of alcohol. Producers were required to supply distributors, who then supplied retailers; consumers could purchase alcohol only from the retailers. Some states, called control states, had a monopoly over the wholesaling and/or retailing of some or all categories of alcohol. In those states, consumers could obtain alcohol only from state-run Alcohol Beverage Control stores. By 2011, there were 19 control states.

The marketing mix model for vodka, therefore, was focused on balancing product line, price, and advertising decisions. Temporary price reductions were generally not allowed by the U.S. government. Further, distribution was not under alcohol producers' control.

Marketing Mix Model

SVEDKA founder Guillaume Cuvelier considered looking into historic U.S. vodka sales to evaluate the effect of new flavors, segment membership, and advertising. Consumer reactions to vodka advertising and pricing probably differed among the super-premium, premium, and value segments. New brand entries also may have had different price and advertising elasticities compared with the established brands. Finally, new flavors could have had a direct effect on vodka sales. Cuvelier wondered if he could quantify the financial value of his product's *Wine Enthusiast* certification and 2002 and 2003 gold medals. Understanding the value generated by each of the three campaigns from 1998 through 2005 would provide a good basis for the design of future campaigns. And identifying brands that directly competed with SVEDKA would allow Cuvelier to effectively allocate marketing resources.

CUSTOMER LIFETIME VALUE

As Don Peppers and Martha Rogers are fond of saying, "Some customers are more equal than others."[1] One way to examine these differences is through customer profit (CP), the difference between the revenues and the costs associated with the customer relationship during a specified period. The central difference between CP and customer lifetime value (CLV) is that CP measures the past and CLV looks forward. As such, CLV can be more useful in shaping managers' decisions but is much more difficult to quantify. Quantifying CP is a matter of carefully reporting and summarizing the results of past activity, whereas quantifying CLV involves forecasting future activity.

Customer Lifetime Value: The Present Value of the Future Cash Flows Attributed to the Customer Relationship

The concept of CLV is nothing more than the concept of present value applied to the cash flows of the customer relationship. The present value of any stream of future cash flows is designed to measure the single lump-sum value, today, of those future cash flows. CLV represents the single lump-sum value, today, of the customer relationship. Even more simply, CLV is the dollar value of the customer relationship to the firm. It is an upper bound on what the firm would be willing to pay to acquire the customer relationship as well as an upper bound on the amount the firm would be willing to pay to avoid losing the customer relationship. If we view a customer relationship as an asset of the firm, CLV would represent the dollar value of that asset.

[1] Don Peppers and Martha Rogers, *Enterprise One to One: Tools for Competing in the Interactive Age* (New York: Currency Doubleday, 1997): 31.

Cohort and incubate

One way to project the value of future customer cash flows is to make the heroic assumption that the customers acquired several periods ago are no better or worse (in terms of their CLV) than the ones currently acquired. We then go back and collect data on a cohort of customers, all acquired at about the same time, and carefully reconstruct their cash flows over some finite number of periods. The next steps are to discount the cash flow for each customer back to the time of acquisition, to calculate the sample customers' CLVs, and then to average all sample CLVs together to produce an estimate of the CLV of each newly acquired customer. This method is referred to as the "cohort and incubate" approach. Equivalently, one can calculate the present value of the *total* cash flow from the cohort and divide by the number of customers to get the average CLV for the cohort. If the value of customer relationships is stable across time, the average CLV of the cohort sample is an appropriate estimator of the CLV of newly acquired customers.

As an example of this cohort-and-incubate approach, Berger, Weinberg, and Hanna (2003) followed all the customers acquired by a cruise-ship line in 1993. The 6,094 customers in the cohort of 1993 were tracked (incubated) for five years. The total net present value of the cash flows from these customers was $27,916,614. These flows included revenue from the cruises taken (the 6,094 customers took 8,660 cruises over the five-year horizon), variable cost of the cruises, and promotional costs. The total five-year net present value of the cohort expressed on a per-customer basis came out to be $27,916,614 ÷ 6,094, or $4,581 per customer. This is the average five-year CLV for the cohort. According to the report:

> Prior to this analysis, [cruise-line] management would never spend more than $3,314 to acquire a passenger…Now, aware of CLV (both the concept and the actual numerical results), an advertisement that [resulted in a cost per acquisition of $3,000 to $4,000] was welcomed—especially since the CLV numbers are conservative (again, as noted, the CLV does not include any residual business after five years).[2]

The cohort-and-incubate approach works well when customer relationships are stationary—changing slowly over time. When the value of relationships changes slowly, a company can use the value of incubated past relationships as predictive of the value of new relationships.

In situations where the value of customer relationships changes more rapidly, firms often use a simple model to forecast the value of those relationships. A model just means some assumptions about how the customer relationship will unfold. If the model is simple enough, it

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[2] Paul D. Berger, Bruce Weinberg, and Richard C. Hanna, "Customer Lifetime Value Determination and Strategic Implications for a Cruise-Ship Company," *Journal of Database Marketing and Customer Strategy Management* 11, no. 1 (2003): 49.

may even be possible to find an equation for the present value of the model of future cash flows. This makes the calculation of CLV even easier as it now requires only the substitution of numbers for the situation into the equation for CLV.

Next, we will explain what is perhaps the simplest model for future customer cash flows and the equation for the present value of those expected cash flows. Although not the only model of future customer cash flows, this one is used the most.

Customer lifetime value model

The CLV formula[3] multiplies the per-period cash margin, *$M*, by a factor that represents the present value of the customer relationship's expected length (**Equation 1**):

$$CLV = \$M \left[\frac{r}{1 + d - r}\right] \tag{1}$$

where r is the per-period retention rate and d is the per-period discount rate.

So, in the model, CLV is a multiple of *$M*, the per-period dollar margin (net of retention spending). The multiplicative factor represents the present value of the expected length (number of periods) of the customer relationship. When $r = 0$, the customer will never be retained and the multiplicative factor is zero. When $r = 1$, the customer is always retained and the firm receives *$M* in perpetuity. The present value of the *$M* in perpetuity turns out to be $\$M \div d$. For retention values in between, the CLV formula tells us the appropriate multiplier.

Example: An Internet service provider charges $19.95 per month. Variable costs are about $1.50 per account per month. With marketing spending of $6 per year, the company's attrition is only 0.5% per month. At a monthly discount rate of 1%, what is the CLV of a customer?

$$\begin{aligned}
\$M &= (\$19.95 - \$1.50 - [\$6 \div 12]) \\
&= \$17.95 \\
r &= 0.995 \\
d &= 0.01 \\
CLV &= \$M \times (r \div [1 + d - r]) \\
CLV &= \$17.95 \times (0.995 \div [1 + 0.01 - 0.995]) \\
CLV &= (\$17.95) \times (66.33) \\
CLV &= \$1{,}191
\end{aligned}$$

[3] Sunil Gupta and Donald R. Lehmann "Customers as Assets," *Journal of Interactive Marketing* 17, no. 1 (2003): 9–24.

Limitations of the CLV model

The model for customer cash flows treats the firm's customer relationships as something of a leaky bucket. In each period, a fraction (1 less the retention rate) of the firm's customers leave and are lost for good.

The CLV model has only three parameters: (1) constant margin (contribution after deducting variable costs including retention spending) per period; (2) constant retention probability per period; and (3) discount rate. Furthermore, the model assumes that in the event the customer is not retained, he or she is lost for good. Finally, the model assumes the first margin will be received (with probability equal to the retention rate) at the *end* of the first period.

One other assumption of the model is that the firm uses an infinite horizon when it calculates the present value of future cash flows. Although no firm actually has an infinite horizon, the consequences of assuming one are discussed below.

The retention rate—and by extension the attrition rate—are drivers of CLV. Very small changes can make a major difference to the lifetime value calculated. Accuracy in this parameter is vital to meaningful results.

The retention rate is assumed to be constant across the life of the customer relationship. For products and services that go through a trial, conversion, and loyalty progression, retention rates will increase over the lifetime of the relationship. In those situations, the model given here might be too simple. If the firm wants to utilize a sequence of retention rates, a spreadsheet model can be used to calculate CLV.

The contribution is assumed to be constant across time. If the margin is expected to increase or decrease with the duration of the customer relationship, the simple model will not apply.

Take care not to use this CLV formula for relationships in which customer inactivity does not signal the end of the relationship. In catalogs, for example, a small percentage of the firm's customers purchase from any given catalog. Don't confuse the percentage of customers active in a given period (relevant for the cataloger) with the retention rates in this model. If customers often return to do business with the firm after a period of inactivity, the previous CLV formula does not apply.

Also take care to match the period of the model to the period of the retention events. If retention happens monthly, for example, then use a monthly model. If retention happens every six months (as for auto insurance), then use a biannual model. If cash flows are spread out within the retention period, then use their present value in the CLV formula.

The infinite horizon assumption

In some industries and companies, it is typical to calculate four- or five-year customer values instead of using the infinite time horizon inherent in the previous formula. Of course, over shorter periods, customer retention rates are less likely to be affected by major shifts in technology or competitive strategies and are more likely to be captured by historical retention rates. For managers, the question is, "Does it make a difference whether I use the infinite time horizon or, for example, the five-year customer value?" The answer to this question is, "Yes, sometimes it can make a difference because the value over five years can be less than 70% of the value over an infinite horizon."

Table 1 calculates the percentages of (infinite-horizon) CLV accruing in the first five years. If retention rates are higher than 80% and discount rates are lower than 20%, differences in the two approaches will be substantial. Depending on the strategic risks that companies perceive, the additional complexities of using a finite horizon may be informative.

Table 1. Five-year CLV as a percentage of infinite-horizon CLV.

	Year					
	1	**2**	**3**	**4**	**5**	**6**
	Retention Rate					
	40%	**50%**	**60%**	**70%**	**80%**	**90%**
Discount Rate	Percent of CLV Accruing					
2%	99%	97%	93%	85%	70%	47%
4%	99%	97%	94%	86%	73%	51%
6%	99%	98%	94%	87%	76%	56%
8%	99%	98%	95%	89%	78%	60%
10%	99%	98%	95%	90%	80%	63%
12%	99%	98%	96%	90%	81%	66%
14%	99%	98%	96%	91%	83%	69%
16%	100%	99%	96%	92%	84%	72%
18%	100%	99%	97%	93%	86%	74%
20%	100%	99%	97%	93%	87%	76%

CLV with initial margin

If you consult other sources on CLV, you may encounter a slightly different formula for CLV (**Equation 2**):

$$CLV_{alternative} = \$M \left[\frac{1+d}{1+d-r}\right] \tag{2}$$

This alternative formula applies to a situation in which the initial cash flow is a certain *$M* received at the *beginning* of the first period. Because of this, this alternative formula always comes out to be *$M* higher than the original formula. It represents the value of the customer if and when acquired.

Prospect Lifetime Value

One of the major uses of CLV is to inform prospecting decisions. A prospect is someone the firm will spend money on in an attempt to acquire him or her as a customer. The acquisition spending must be compared not just with the contribution from the immediate sales it generates, but also with the future cash flows expected from the newly acquired customer relationship (the CLV). Only with a full accounting of the value of the newly acquired customer relationship will the firm be able to make informed economic-prospecting decisions.

The expected prospect lifetime value (PLV) will be the value expected from each prospect minus the cost of prospecting. The value expected from each prospect will be *a*—the expected fraction of prospects who will make a purchase and become customers—times ($\$M_0 + CLV$), where $\$M_0$ is the average margin the firm makes on the initial purchases net of any marketing spending used to attempt to retain the customer at the end of the first period. The cost will be *$A*, the amount of acquisition spending per prospect. The formula for expected *PLV* is shown in **Equation 3**:

$$PLV = a(\$M_0 + CLV) - \$A \tag{3}$$

If *PLV* is positive, the acquisition spending is a wise investment. If *PLV* is negative, the acquisition spending should not be made.

The *PLV* number will usually be very small. While *CLV* is sometimes in the hundreds of dollars, *PLV* can come out to be only a few pennies. Just remember that *PLV* applies to prospects, not customers. A large number of small- but positive-value prospects can add to a considerable amount of value for a firm.

Example: A service company plans to spend $60,000 on an advertisement reaching 75,000 readers. If the service company expects the advertisement to convince 1.2% of the readers to take advantage of a special introductory offer (priced so low that the firm makes a $10 margin on this initial purchase) and the CLV of the acquired customers is $100, is the advertisement economically attractive?

Here, *$A* is $0.80, *a* is 0.012, and $\$M_0$ is $10. The *PLV* of each of the 75,000 prospects is

$$\begin{aligned} PLV &= a(\$M_0 + CLV) - \$A \\ &= 0.012 \times (\$10 + \$100) - \$0.80 \\ &= \$0.52 \end{aligned} \tag{4}$$

The expected lifetime value of a prospect is \$0.52. The total expected value of the prospecting effort will be 75,000 × \$0.52 = \$39,000. The proposed acquisition spending *is* economically attractive.

If we are uncertain about the 0.012 acquisition rate, we might ask what the response rate from the prospecting campaign must be in order for it to be economically successful. We can get that number using Excel's Goal Seek function to find the *a* value that sets *PLV* to zero. Or we can use a little algebra and substitute \$0 in for *PLV* and solve for *a*:

$$a_{be} = \frac{\$A}{\$M_0 + CLV}$$
$$= \$0.80 \div (\$10+\$100)$$
$$= 0.007273. \qquad (5)$$

The acquisition rate must exceed 0.7273% for the campaign to break even on an NPV basis.

Issues with PLV

Perhaps the biggest challenge in calculating PLV is estimating the CLV. The other terms (acquisition spending, expected acquisition rates, and initial margin) all refer to flows or outcomes in the near future, whereas CLV requires longer-term projections.

Another caution worth mentioning is the decision to spend money on customer acquisition whenever PLV is positive. This rests on an assumption that the customers acquired would not have been acquired had the firm not spent the money. In other words, this approach gives the acquisition spending "full credit" for the subsequent customers acquired. If the firm has several simultaneous acquisition efforts, for example, dropping one of them might lead to increased acquisition rates for the others. Situations such as these (where one solicitation cannibalizes another) require a more complicated analysis.

The firm must be careful to search for the most economical way of acquiring new customers. If there are alternative prospecting approaches, the firm must be careful not to simply go with the first one that gives a positive projected PLV. Given a limited number of prospects, the approach that gives the highest expected PLV should be used.

Finally, we want to warn you that there are other ways to perform the calculations necessary to judge the economic viability of a given prospecting effort. Although these other approaches are equivalent to the one presented here, they differ with respect to what is included in CLV.

Some approaches will include the initial margin as part of CLV. For our service company example, this approach would say that the CLV is \$110.

Another common approach includes both the initial margin and the expected acquisition cost per acquired customer as part of the CLV. For the service company example, this CLV equals $110 – ($60,000 ÷ 900) = $43.33. Here, 900 is the expected number of new customers and $60,000 ÷ 900 is the expected cost per new customer. The $43.33 is the expected value of the prospecting effort expressed on a per-customer-acquired basis. If this CLV is positive, the prospecting effort is economically attractive.

Notice that $43.33 times the 900 expected new customers equals $39,000, the same total net value from the campaign calculated in the original example. The two ways to do the calculations are equivalent.

Retention and Customer Lifetime Value

Reichheld and Sasser (1990)[4] helped popularize the idea that customer retention is an important driver of firm financial success. They reported that "reducing defections by 5% boosts profits 25% to 85%."[5] Rather than rely on the Reichheld and Sasser percentages, we offer three approaches for quantifying the economic benefits of increased retention for a given firm.[6]

In the first approach, the firm might build an electronic spreadsheet model to forecast future company profits and cash flows as a function of a retention rate or schedule of retention rates. One could then change the retention rate or schedule of retention rates and observe what happens to profits and cash flows. These "what-if" analyses conducted using a spreadsheet model would be one way to quantify the benefits of increased retention. If the firm thought, for example, that increased retention would reduce the need for future acquisition spending, that linkage could be built into the model and captured in the what-if analyses.

The second and third approaches ask how increased retention affects the lifetime value of the customer. Whereas the firm-level spreadsheet approach above projects the future stream of company profits and cash flows, CLV accounts for the dollar value of the future cash flows attributed to the customer—either a single customer or (more than likely) an average customer.

In the second approach, the firm might build an electronic spreadsheet model of future cash flows associated with the customer relationship. That model might allow for margins and retention rates to increase with customer tenure. The present value of the projected future cash flows would be the estimated CLV. To quantify the economic benefits of increased retention, once again the firm could conduct what-if sensitivities using the model of customer cash flows.

[4] Frederick F. Reichheld and W. Earl Sasser Jr., "Zero Defections: Quality Comes to Services," *Harvard Business Review* (September–October 1990): 105–11.

[5] Reichheld and Sasser Jr.

[6] Phillip E. Pfeifer and Paul W. Farris, "The Elasticity of Customer Value to Retention: The Duration of a Customer Relationship," *Journal of Interactive Marketing* 18, no. 2 (Spring 2004): 20–31.

For example, one might multiply the schedule of retention rates by 1.01 and recalculate the CLV. The resulting number would represent the CLV if all retention rates increased by 1%.

In the third approach, the firm might assume constant margins and retention rates and perform what-if analyses directly on the formula for CLV presented earlier in this note.

Example: Consider again the customer relationship where $\$M = \$17.95$, $d = 0.01$, and $r = 0.995$. The calculated *CLV* was \$1,191. Now suppose the firm expected r to increase to 0.996 as a result of several recent customer-relationship-management initiatives.

To quantify the benefits of the expected increased retention, we calculate CLV for $r = 0.996$ and get $CLV = \$1,277$ (an increase of about 7.2%).

When using the CLV formula, remember the timing assumptions inherent in this formula. The formula applies to current customers whose next cash flow occurs in one period in the event they are retained. This timing assumption is conservative because, in actuality, the firm's current customers will be spread throughout the renewal cycle. For some customers, the renewal event will be imminent, not a full period away.

The change in CLV for a change in retention rate is a measure of the increase in dollar value of the firm's current customer base. This dollar value does not translate directly to an equivalent increase in yearly profits because there are many other factors affecting firm profits. If the firm wants to measure the impact of increased retention rate on yearly profits, a firm-level model described in the first approach is required.

The firm should also remember that increases in retention rate not only affect the value of the firm's current customers, but also the value of the firm's current prospects whenever the increases in retention rate are expected to also apply to customers the firm will acquire in the future. The economic benefits of increased retention must be compared with the costs required to achieve the increased retention rates in order to make a sound investment decision.

Conclusion

CLV provides firms with a forward-looking metric that combines customers' retention rate, marketing spend, and cash flows. The metric is a good tool to assess the effects of increasing retention rates on future customer value and the amount a firm should spend on customer acquisition. When marketing spend is connected to retention rates and future cash flows, the metric provides a mechanism for firms to optimize marketing spending.

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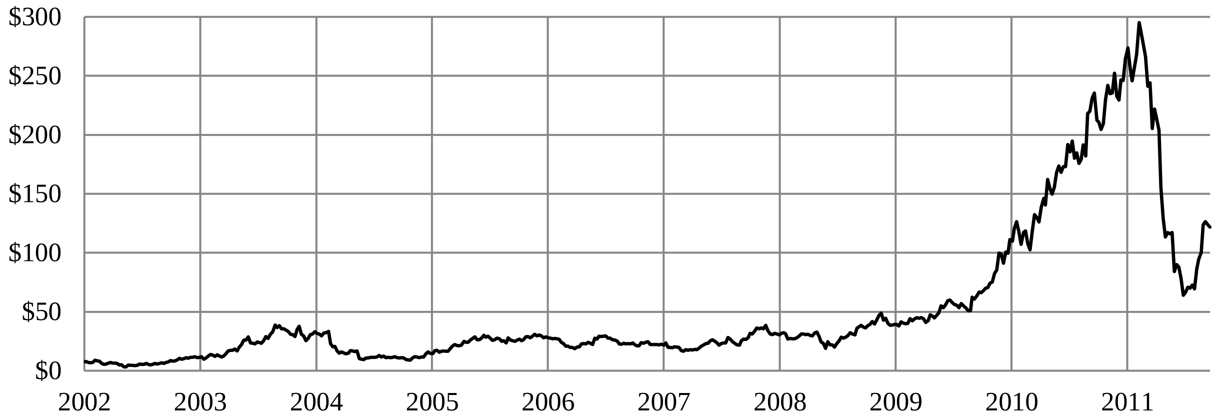
Netflix, Inc.: The Customer Strikes Back

Three years after earning his MBA, Hunter Keay was starting to make a name for himself at a leading investment bank when, in February 2012, some of his clients grew increasingly anxious about the value of their holdings in Netflix, Inc., the subscription-based media-distribution company. Six months earlier, Netflix had announced a plan to split its on-demand video streaming and DVD mail delivery into two businesses (Qwikster for DVD rental by mail and Netflix for video streaming) and to increase the price of its most popular service. But in the face of near-universal criticism, Netflix had abandoned the plan within a month, only to lose 800,000 subscribers and half its stock value (**Figure 1**). Keay's clients who held Netflix stock wanted to know what remained of their investment.

Figure 1. Netflix stock price and volume, March 2002 to February 2012.



Data source: Yahoo! Finance.

To determine a more accurate value of Netflix stock, rather than apply one of the standard methods favored by his firm, Keay was considering the use of *customer lifetime value* (CLV). He was not certain that the metric applied in this instance or whether the firm even considered it valid, nor was he certain how CLV related to the more accepted methods. He was certain about one thing, though: new technologies were transforming the industry and the ways customers received video content. The question was whether *Netflix 2: The Sequel* would ever be as popular as the original.

An Industry Driven by Technology

The video-rental industry had been substantially altered by technological developments outside the industry. Major milestones included DVDs that could be ordered via the Internet and that were delivered by mail, video streaming, and, lately, kiosks.

The traditional retail rental store

The advent of videotape, acceptance of the VHS cassette standard, and subsequent affordability of home videocassette players in the 1980s brought with them the proliferation of the movie-rental business. By the 1990s, the majority of market share had consolidated to a few participants with similar business models competing on selection, price, and especially location. National chains such as Blockbuster and Hollywood Video grew by staking claims at strategic locations with adequate population density. By 1990, Blockbuster professed to have a store within a 10-minute drive of 70% of the U.S. population. Mom-and-pop video stores survived by finding locations the chains did not seek.

Movie rental required that a customer leave his or her home with the intention of renting, then make a spontaneous decision based on what was available. The cost of a video rental ranged from $3.00 per week for older movies to $6.00 per three days for new releases (allowing for weekend viewing when rented on Friday, the most popular day). Small mom-and-pop stores typically had a collection of a few hundred videos for rental; a Blockbuster store had about 2,500 titles. A store's video paid for itself after 13 rentals, so films with mass appeal were the norm; nearly 70% of all films rented at Blockbuster were new releases. Limited selection and stock-outs were a common concern, as was the relative convenience of store hours.

Late returns were a thorny problem: a movie could not be rented until it was back on the shelf, and a scarcity of titles might deter a customer from returning. So video stores charged late fees, which monetized the delay and encouraged the customer to return movies promptly. In reality, as one commentator noted, late fees called attention to customer failure, in the manner of "a disapproving librarian tallying up 35 cents in overdue fines while floating the unspoken accusation you were irresponsible on top of everything else."[1] When Blockbuster eventually dropped many forms of late fees, the move resulted in a charge to revenue of $400 million. The brick-and-mortar value proposition was eroding.

DVD by mail

DVD mail service started to gain popularity in the early 2000s. The subscribing customer selected a movie on a website, and a DVD would arrive at their home in about one business day. The customer could keep the DVD as long as he or she liked, then mail it back to the provider in a prepaid envelope. By selecting multiple movies and arranging them in order of priority in an online queue, the customer could ensure prompt delivery of subsequent selections and always have something on hand to watch as opportunities arose. Subscription tiers were based on how many movies a customer could receive simultaneously and were priced accordingly, starting at $7.99 per month for one movie at a time. (See **Exhibit 1** for a complete pricing comparison.)

[1] Tara Lemmey, "Push the Positive for Customers," Bloomberg Business online, September 12, 2005, http://www.bloomberg.com/bw/stories/2005-09-12/push-the-positive-for-customers (accessed July 21, 2015).

Video on demand

Video on demand (VOD) was content distribution via Internet-connected television, computer, or mobile device. The customer selected a movie from an online menu and, within seconds, the movie began streaming to his or her device; the customer could view the content as it was downloaded, rather than waiting for the complete file, which otherwise could take almost as long as the running time of the film. No exchange of a data-storage medium was required, so stock-outs and late fees were avoided, and a significantly larger and more eclectic catalog could be offered.

Kiosk rentals

Movie-rental kiosks were freestanding dispensers of DVDs located in high-traffic areas with extended—sometimes 24-hour—access, such as convenience stores, grocery stores, and fast-food restaurants. Redbox, the dominant player, founded in 2003, was originally funded by McDonald's. As of 2012, Redbox claimed to have rented 1.5 billion movies from 30,000 kiosks nationwide and to operate a kiosk with a five-minute drive of two-thirds of the U.S. population. Its only significant competitor, albeit a much smaller player, was Blockbuster's "Blockbuster Express" kiosks.

Kiosks revolutionized the rental price point (about $1.00 per night per movie) and changed consumer renting behavior by eliminating the planning ahead required by DVD-by-mail services and the need to go to another location required by rental stores. Plus, 24-hour access freed customers from time constraints. Selection, however, was limited by two major shortfalls: the physical space inside the kiosk and delayed releases to kiosks by movie studios wary of cannibalizing DVD sales.

A New Range of Business Models

As content-delivery methods increased, an industry participant could employ different pricing heuristics across different channels and different end-user content licenses. As such, revenue model, delivery method, and content licensing were dimensions by which each participant might be assessed (**Figure 2**).

In terms of revenue, a business was either pay-per-view or monthly subscription. Depending on the delivery method, the one-time fee of the pay-per-view model would entitle the customer to rent one DVD by mail or online streaming access for a finite time period of time. In the case of purchase, a one-time fee entitled the buyers to indefinite ownership of streaming content or of an actual DVD.

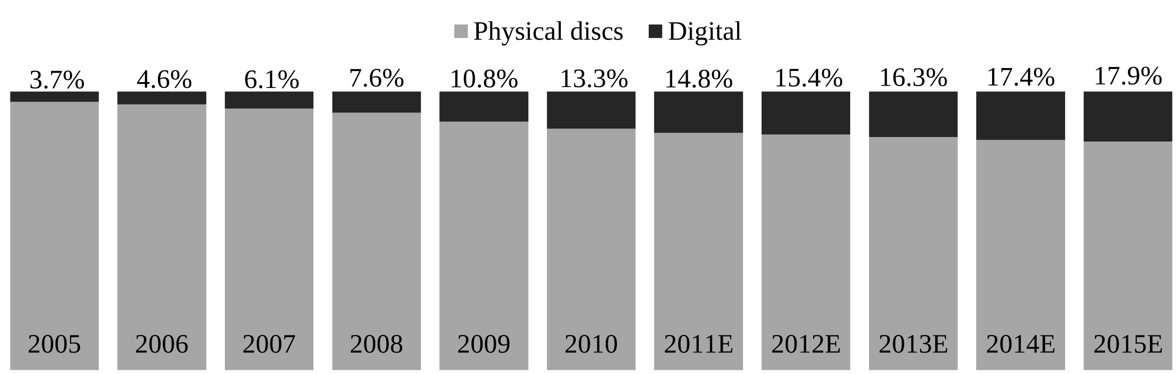
Figure 2. Perceptual market map for the VHS and digital eras.

	Revenue model		**Delivery method**		**Content licensing**	
Before 2000 (VHS)	À la carte	Subscription	Streaming	VHS	Rent	Buy
Blockbuster	•			•	•	
Hollywood Video	•			•	•	
Video Update	•			•	•	
Local Video Store	•			•	•	
After 2000 (digital)				DVD		
Amazon Prime		•	•		•	
Amazon Instant Video	•		•		•	•
Blockbuster	•	•	•	•	•	•
CinemaNow	•		•		•	•
DVD Café	•	•		•	•	•
Greencine		•		•	•	
Hulu	free	free	•		•	
Hulu Plus		•	•		•	
iTunes	•		•		•	•
Netflix		•	•	•	•	
Redbox	•			•	•	
VUDU	•		•		•	

Data source: Company websites.

Content was either delivered by physical DVD or streamed over the Internet from the service's website to the user's computer or ancillary television device, sometimes called a *streaming player*. Physical discs were still the dominant medium, but increased digital access was expected to continue (**Figure 3**). The downward pressure on physical discs was somewhat mitigated by the increasing popularity of kiosk rental systems such as Redbox. A user's right to content varied by service provider and plan, but generally fell into one of three categories: rental for a finite period of time, outright purchase for unlimited personal use, or access to an entire online library from which content could be streamed.

Figure 3. Digital streaming as percentage of content delivery, 2005 to 2015 (projected).



Data source: Mintel/Digital Entertainment Group, May 2011.

Netflix: Delivering Goose Bumps

Reed Hastings founded Netflix in 1997 in Los Gatos, California, after paying $40 in late fees to the local video store for *Apollo 13*, and later asking, "How come movie rentals don't work like a health club, where, whether you use it a lot or a little, you get the same charge?"[2] The key was to let people watch movies whenever they wanted. The Netflix model was simple: movies that consumers ordered from Netflix's website were shipped to their houses. Once consumers watched the movies, they returned them to Netflix in envelopes that were shipped along with the DVDs. Netflix claimed that it could ship videos to most customers in less than 24 hours.

Netflix's first innovation, in December 1999, was to eliminate late fees. Customers paid a fixed monthly fee of about $16, rented as many as four movies in a single order, and kept films as long as they wanted. Technically, the longer customers kept films, the lower Netflix's shipping cost per rental. Customer retention under this system, however, depended on customers renting more movies per month: the more rentals per month, the more value customers placed on the service. As Hastings stated, "If [the customers] rent just two movies a month, they may decide it is not worth it."[3] This made Netflix's movie recommendation system extremely important: good recommendations increased queue length, which increased retention, which increased CLV.

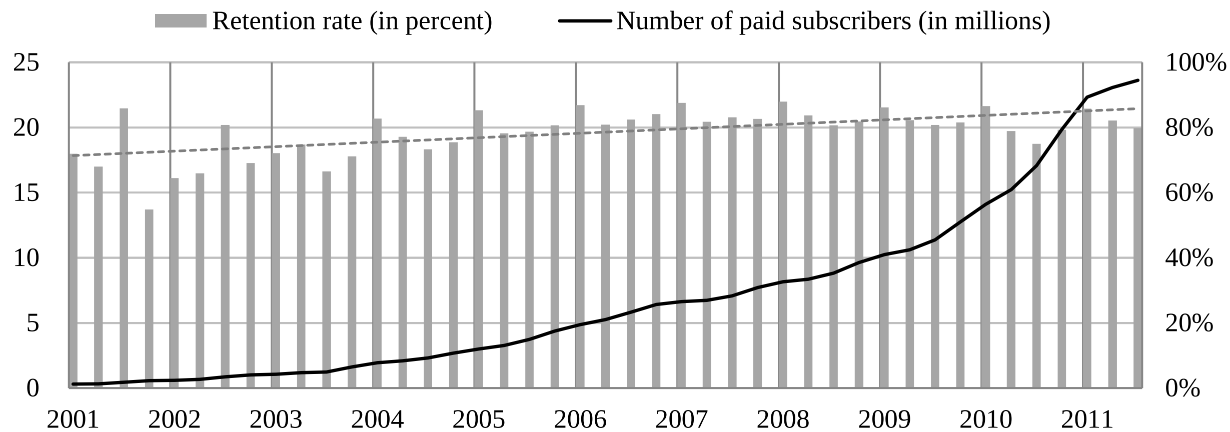
To expand its customer base and reduce its reliance on the most popular films, Netflix invested significantly in data-mining technology. Netflix developed a simple but effective movie-recommendation algorithm that compared each user's purchase to those of customers with similar tastes and then suggested films that were highly rated and unseen. These reviews, together with a catalog of close to 85,000 titles, held new releases to only 30% of rentals, and 95% of Netflix's titles were rented every quarter. Netflix was picking up revenue from a far broader distribution of preferences than a retail store could ever offer.

As the Netflix catalog grew, the recommendation system became simpler and more robust. In January 2000, Netflix introduced a new simple and accurate recommendation system called CineMatch. Each customer was prompted to rate certain movie genres and specific movies on a one- to five-star scale. The program found others in its database with similar preferences and then offered a predicted star value for each movie. As the customer rated more films, the accuracy of the data improved substantially. As Hastings stated, "Over 50% of our traffic comes via the recommendation system. It requires a lot of database work done in real time."[4] By 2007, Netflix had close to 1 billion movie reviews, with customers reviewing an average of 200 movies each.

CLV depended on the extent to which Netflix could leverage its large catalog by encouraging customers to rent more. Its target for per-customer monthly orders was five, the corporate average. Special promotions encouraged current customers to refer the service to friends and family; efforts resulted in an upward trend in customer retention (**Figure 4**).

[2] Chris Taylor, "The Movie Is in the Mail," *Time*, March 18, 2002.
[3] Alan Cohen, "Netflix: DVDs at Your Door," *PC Magazine*, February 19, 2003.
[4] Cohen.

Figure 4. Paid subscribers and retention rate, March 2001 to December 2011.



Data source: Netflix Q1 earnings report, 2012.

Coming Soon

Keay asked his analyst to compile the financial data required to calculate CLV at Netflix, but a considerable amount of work lay ahead. Was CLV an appropriate approximation of firm value in this setting? Did CLV track with market capitalization, discounted cash flows, or other traditional firm-valuation techniques? How sensitive was CLV to various operational and strategic changes? And what role might be played by changes in technology? With such a public call on a volatile stock at this point in his young career, Keay could not afford to miss.

Exhibit 1

Netflix, Inc.: The Customer Strikes Back

Pricing Comparison (per month unless otherwise indicated)

	Netflix	Amazon Prime[1]	Blockbuster	iTunes[2]	Redbox[3]
Rental subscription					
Two DVDs/month, one out at a time	$4.99				
Unlimited DVDs					
One out at a time	$7.99		$9.99		
Two out at a time	$11.99		$14.99		
Three out at a time			$19.99		
À la carte (VOD only)			$3.99	$3.99	
Unlimited VOD	$7.99	$6.58			
Unlimited VOD + DVDs					
VOD + one DVD out at a time	$15.98				$1.00
VOD + two DVDs out at a time	$19.98				
VOD + three DVDs out at a time	$23.98				
VOD + four DVDs out at a time	$29.98				
Purchase (à la carte only)					
VOD			$15.99	$14.99	
DVD			$14.99		

Data source: Company websites.

[1] Includes digital books and free shipping on items purchased from Amazon.com.
[2] Per movie.
[3] Per movie per night.

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RETAIL RELAY (A)

The last-mile delivery cost kills most home-delivery businesses. I knew we could find a better way.

—Zach Buckner, CEO of Retail Relay

During the summer of 2007, Zach Buckner, the 31-year-old founder and CEO of Retail Relay, was again confronted with an ongoing frustration of daily suburban life. After his third trip to a local hardware store to get supplies for the same home improvement project, Buckner realized that a one-day project had now effectively become an all-weekend affair. He had spent more time shopping than installing new wiring in his 1930s-era house. Buckner had studied electrical and systems engineering and completed many consulting assignments for companies looking to improve their business operations. He drew on that knowledge and experience to come up with the concept of Retail Relay (**Figure 1**). And a new paradigm for online shopping was born.

Figure 1. Retail Relay's delivery trucks, which also served as moving billboards.

Source: Case writer photograph.

Although online retailing was certainly not a new concept, Buckner's approach was unique. His overall objective was to provide a solution to a problem faced by all Americans: time

This case was prepared by Ronald T. Wilcox, Professor of Business Administration, and Kelly Brandow, Case Writer. It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

wasted, inefficiencies, and costs caused by the daily need to run errands. His initial concept was to provide an online means for consumers to order and purchase goods from a variety of local retailers (i.e., grocers, hardware stores, clothiers), minimizing the burden of making trips to individual stores. Although the obvious solution was to provide convenient delivery service to customers' homes, Buckner soon realized there was no way to make this economically feasible.

Many online businesses that had entered the home-delivery market had failed. Perhaps the most spectacular of these early failures was Webvan, a grocery home-delivery service that at its height operated in 10 metropolitan areas in the United States. Webvan built a billion-dollar order-processing, warehousing, and delivery infrastructure. Its revenues and profits never came close to covering its capital outlay, however, and in 2001, it filed for bankruptcy protection.

But not all these home-delivery businesses had failed. Bolstered by substantial growth in both online retailing and the market for fresh, organically produced food items, Long Island food purveyor Fresh Direct had enjoyed considerable success.[1] Founded in 1999, this online grocery business was built on offering custom-prepared groceries and meals for its customers. By sourcing food items directly from local farms, dairies, and fisheries and preparing meats, breads, and so on in an on-site warehouse facility, Fresh Direct was able to reduce transit time and improve the quality and freshness of its products, while also reducing costs by eliminating the need for a middleman. In that sense, Fresh Direct acted in many ways like a traditional grocery retailer, buying direct and carrying inventory. Though its delivery area was still limited mainly to Manhattan, Brooklyn, and Queens, there were plans to expand.

Buckner was determined not to repeat the mistakes of others. To make Retail Relay successful, it would be imperative to cut out "last-mile delivery costs" and to minimize up-front working capital requirements. Last-mile delivery costs greatly reduced operating margins. Getting a truckload of products to a single neighborhood or workplace location was not nearly as costly as paying for drivers and trucks to bring products to individual homes. Likewise, a simple initial distribution system would not require the kind of "Willy Wonka operation" that had strained the financial viability of so many other businesses.[2] Fresh Direct had been able to make its more expensive warehouse and home-delivery system work, but it operated in a densely populated area of New York City. Buckner wanted to find several locations that were convenient for many customers, both in location and in ease of order pickup. These pickup locations would be the "relay" point for the grocery items on their journey from farm or store to the customer's home. If these cost-reduction measures were successful, they would allow Retail Relay to provide this service to customers without charge, which effectively meant customers would pay the same price for these items as if had they had shopped at the retailers' stores themselves.

[1] U.S. sales of organic foods stood at about $6.2 billion in 2009, after several years of growth rates exceeding 20% per year.

[2] Zach Buckner used the phrase "a Willy Wonka operation" in reference to the movie *Willy Wonka and the Chocolate Factory* as a way of implying a highly elaborate and automated system.

Although the original plan was to sell much more than grocery-type items, initial sales feedback confirmed that local, natural, organic, and healthy foods and household items were by far the best-selling categories. The custom leather belts did not sell. Neither did electrical wiring. Retail Relay soon narrowed its business concept, becoming a grocery- and farm-product retailer.

Even though the company abandoned the idea of selling a vast selection of nongrocery items early on, it was still important to offer customers a wide selection of grocery items. A narrow selection would not achieve the goal of reducing the amount of time customers spent grocery shopping because they might still have to stop at a store to pick up items Retail Relay did not offer. Customers wanted to buy free-range chicken and freshly picked English peas, but they also wanted to buy paper towels and laundry detergent—and, if possible, they wanted to avoid a supermarket trip entirely. While signing up large grocery retailers as suppliers had the advantage of quickly producing a large available assortment, these large retailers had little to gain and potentially much to lose by acting as Relay's suppliers. Sales through Relay might cannibalize their own in-store sales. For this reason, the initial push for suppliers focused on smaller, boutique-type retailers, restaurants, and local farms. For smaller retailers and farms, Relay offered a promising new vehicle through which to reach a previously untapped consumer market with its goods, and their risk of cannibalization was small.

When putting forth proposals to local businesses, Retail Relay experienced overwhelming acceptance, with a 100% positive response rate from the retailers it approached with this collaborative opportunity. Retail Relay enlisted more than 40 unique suppliers, covering a wide assortment of grocery items. Large supermarkets such as Whole Foods, however, were not used as suppliers.

Retail Relay Operations

Retail Relay set up initial operations in Charlottesville, Virginia, a city that had a population of 50,000 and that was home to the University of Virginia as well as several other large private and government employers. Although pockets of poverty existed in Charlottesville, significantly more than the average number of residents could be described as having a high level of income and/or a high level of education.[3] It also had an unusually high proportion of residents who were interested in local and organic food. Retail Relay's management team believed that Charlottesville was an ideal location in which to test its concept.

[3] "Demographics," City of Charlottesville, http://www.charlottesville.org/Index.aspx?page=576 (accessed July 21, 2011).

The typical customer order and product pickup process followed six discrete steps:[4]

1. Customers submitted orders and paid for them online at RetailRelay.com, selecting from what evolved into an assortment of mostly grocery and home products. Customers wanting to pick up their orders the next day had to place them by midnight the night before.
2. Orders were downloaded by Retail Relay immediately after midnight and were then broken down and transmitted to participating retailers.
3. Retailers used these orders to pack and sort bags by customer number.
4. Orders were picked up by a Retail Relay driver the following morning and returned to the warehouse, where they were manually re-sorted.
5. Orders from multiple retailers were re-sorted by customer and repacked onto the truck in the appropriate temperature zone (shelf-stable, refrigerated, frozen) (**Figure 2**). Any one customer might have bags from several retailers and multiple bags from a given retailer.
6. Finally, orders were transported to the customer pickup location in a Retail Relay truck.

Figure 2. Retail Relay driver loading the truck and waiting at a pickup location.

Source: Case writer photographs.

Although not as cost prohibitive as home delivery, collecting, sorting, and delivering products to the pickup location cost money. Because individual suppliers removed ordered products from their own shelves and had them ready for the Retail Relay driver near the front of the store, it took drivers very little time to collect merchandise from individual suppliers. It took very little time for the driver to move from one supplier to the next during the collection process because the community was relatively small. Overall, the costs associated with collecting merchandise from suppliers were negligible.

[4] Retail Relay did offer a fee-based home-delivery option, but this constituted a small part of its business.

Sorting products by customer and distributing them to customers was costly. Because this sorting process was very labor-intensive, an individual worker could sort only about $400 of product per hour. The cost of labor, both for workers who sorted and for truck drivers, was about $15 per hour. Unlike product collection, distribution was not a quick process. Drivers had to drive to the pickup location and wait for three to four hours while customers came by to pick up their orders. On average, a driver would spend about five hours transporting product from the warehouse to the pickup location, setting up at the location, waiting for customers to pick up their orders, and then returning to the warehouse. A fully loaded truck could carry about $3,200 of merchandise and made deliveries about 200 days per year. The trucks themselves were utilitarian, lacking the comforts of longer-haul vehicles. They were also inexpensive to operate. Retail Relay estimated that the total cost of a truck, including maintenance and fuel, was about $3,000 per year.

Prices and Promotions

The basic contract with suppliers stipulated that suppliers had to sell products to Retail Relay at 15% less than their in-store shelf price. The retail price to customers was set to the current shelf price at the supplier's brick-and-mortar establishment. Suppliers were required to enter their own product prices—using in-house-developed iPhone, BlackBerry, and Android applications—into Retail Relay's ordering system. While it was possible for Retail Relay to audit its system to make sure its prices were indeed the same as an individual supplier's regular shelf prices, it was more difficult to know whether every deal price offered at a supplier's store was passed through to Retail Relay customers. As a practical matter, management believed that some suppliers were more diligent than others in making sure their Retail Relay price matched their true shelf price.

Retail Relay engaged in a limited amount of price promotional activity. New customers generally received a coupon for 10% off their next purchase, printed on the receipt of their first purchase. On the second purchase, they received a 5% discount coupon for a third purchase. The redemption rate of these coupons on qualified purchases was high, around 80%. The rationale behind these first- and second-purchase coupons flowed from two studies that Retail Relay did involving purchase data from customers. The first, a small pilot study, tracked the purchase activity of 81 randomly chosen customers who had made their first purchase with Retail Relay before June 2009. In constructing the pilot study, management wanted to be sure it could track these individuals over a period long enough to observe many purchase occasions. The company was growing very quickly, and many of their customers were new and, as such, had made only a small number of purchases. Given that the average interpurchase interval for individuals in this sample was approximately three weeks, and that the end of the time frame for analysis was February 2010, it seemed reasonable to restrict the pilot group to those who had made their first purchase at least nine months earlier. Descriptive statistics for this pilot study are provided in **Exhibit 1**.

Two things stood out in the results of this pilot study. First of all, many people seemed to be purchasing from Retail Relay once and not returning to make another purchase. Of the 81 customers who tried Retail Relay, 32% never returned to make a second purchase. Second, the average size of the basket of goods purchased increased once an individual became experienced in dealing with Retail Relay. The average size of an individual's first purchase was $49.51, whereas someone who had ordered from Retail Relay frequently made an average purchase of $92.91 on their 20th purchase occasion. Both of these findings suggested to management that offering promotions for the second and third purchase occasion to get new customers "over the hump" might be an effective way to retain those customers.

Once the results of the pilot study were known, Retail Relay conducted a more extensive study using 587 randomly selected customers and choosing them regardless of when they had made their first purchase. The managers hoped this new, much larger sample size would provide more reliable results than those of the pilot study. Descriptive statistics for this study can be found in **Exhibit 2**. Indeed, the more extensive study showed an even larger attrition rate between the occasion of the first and second purchase—45%—a worrisome number for management. The results of the more extensive study were not convincing to everyone on the management team. In particular, some were concerned that using a sample containing many individuals who had only recently become customers would bias the analysis because management would not be able to observe anything other than their first few purchase occasions. Whether the pilot study or the larger study provided a more accurate depiction of customers' purchase patterns was an open question.

Retail Relay tested the value of home-delivered flyers as well, distributing 2,000 of them to homes in a Charlottesville subdivision. The flyers contained a coupon for 10% off the total price of a Retail Relay order. The cost of this door-to-door program, including printing, transportation, and labor, was approximately $1,200 and produced a total of seven uses, all of which were new customers.

Retail Relay also tested coupons inserted in Valpak "blue envelopes"—mailers that contained coupons and promotional offers from many companies, most of them local. Retail Relay's coupon offered $5 off any purchase of $25 or more and $15 off a purchase of $100 or more. An example of the Valpak insert can be found in **Exhibit 3**. Purchasing insert coverage across three separate mailings at a cost of $1,100, Retail Relay was able to reach approximately 60,000 homes in the greater Charlottesville area. Based on coupon redemptions, which required customers to input a promotional code when they submitted their online order, and previous purchase data, management determined these Valpak inserts were redeemed by 58 new customers and 10 existing customers.

Management wanted to determine the profitability of these promotions. An important part of this analysis would be the determination of customer lifetime value (CLV), a metric that assigned a dollar value to a potential new customer. A CLV analysis of its customer-level data would allow Retail Relay to answer the question, "If I acquire a new customer, on average how much money is that customer really worth?" The **Appendix** provides a description of how to apply CLV analysis to the data contained in the supplemental Excel spreadsheet accompanying the case (UVA-M-0784X).

New Customer Acquisition and Retention

Aside from its limited foray into direct-to-consumer price promotions, Retail Relay employed several tactics to recruit new customers and retain existing ones. It set up informational booths at various community functions around Charlottesville (e.g., Discovery Museum Fair, Vegetarian Festival, and Virginia Festival of the Book), and management was available for local talk radio programs that catered to Retail Relay's target audience. But by far its largest promotional investment, in terms of both time and money, was its e-mail and social media campaigns. Beginning each Sunday, promotional Retail Relay e-mails were distributed to thousands of existing customers as well as to others whose e-mail addresses had been obtained during other promotional activities. E-mail delivery was staggered to ensure that existing customers would receive messages one day prior to their regular order day to serve as a reminder as well as to offer special information in a timely manner.[5] A sample promotional e-mail can be found in **Exhibit 4**. To further promote awareness through this medium, Retail Relay established partnerships with large local employers who sent e-mail blasts out to its employee base, offering exposure to an expanded group of potential customers. Individuals could also become fans of Retail Relay on Facebook, and its Facebook page was regularly updated with new information on suppliers, recipe suggestions, and comments on what produce was starting to come in season.

Through all this activity, Zach Buckner and his recently hired new president, Arnon Katz, a 2009 graduate of the Darden School of Business, wondered if the customer acquisition and retention activities were really worth what they cost the business in time, money, and aggravation. As the customer base grew, perhaps they should simply allow word-of-mouth advertising from existing customers to filter through the rest of their target audience. Retail Relay's growth rate was robust, averaging 25% per month over the previous six months, and ramping up the home-delivered flyers or Valpak mailers did not seem to be a great use of time and money, particularly in the small market of Charlottesville.

The Richmond Expansion

In its Charlottesville birthplace, Retail Relay was enjoying robust and profitable growth, but Buckner and Katz had already made plans to expand to other locations. On the immediate horizon was a planned expansion in summer 2010 into the Richmond, Virginia, market. Katz was put in charge of making plans for the expansion, and there was much to consider.

[5] Customers often developed a regular pattern in their orders whereby it was possible to predict the most likely day of the week for their purchases.

The City of Richmond anchored a metropolitan area of approximately 1.2 million people; the population of the city proper was slightly more than 200,000. The city and surrounding metropolitan area were more economically diverse than Charlottesville. This market would present its own set of challenges. New pickup locations would have to be selected, a new sorting facility established, and—because Richmond was 70 miles from Charlottesville—a new supplier base developed. As Katz assessed the situation, he considered whether to enter the market with an aggressive customer acquisition effort, spending the profits the Charlottesville market had generated on promotions designed to gain rapid market penetration. He asked himself how much money a new customer was really worth and what the most effective promotional ideas for reaching new customers were.

On the flip side, Retail Relay could start with just a couple of pickup locations and let the business grow through the same word-of-mouth advertising that had previously been successful. Katz looked over the sizable amount of purchase and promotional data he already had and thought about how he could use this information to better market the company's products in Richmond. If Retail Relay had worked well in Charlottesville, then perhaps it would work well anywhere.

Exhibit 1

RETAIL RELAY (A)

Descriptive Statistics of Customer Purchases Conditioned on How Many Times An Individual Has Ordered from Retail Relay (Pilot Study)

Order Number	**Total Number of Observations in the Data**	**Conditional Probability of Observing Purchase Occasion *t + 1* in the Data if Occasion *t* is Observed***	**Average Dollar Amount of Purchase**
1	81	NA	$ 49.51
2	55	55 ÷ 81 = 68%	$ 62.28
3	44	44 ÷ 55 = 80%	$ 57.01
4	34	77%	$ 62.03
5	31	91%	$ 63.06
6	28	90%	$ 72.90
7	23	82%	$ 60.30
8	21	91%	$ 63.68
9	20	95%	$ 72.04
10	19	95%	$ 67.89
11	17	89%	$ 70.07
12	17	100%	$ 82.48
13	16	94%	$ 82.17
14	15	94%	$ 61.12
15	14	93%	$ 65.79
16	13	93%	$ 82.29
17	13	100%	$ 65.32
18	13	100%	$ 99.20
19	13	100%	$ 73.74
20	12	92%	$ 92.91
21	10	83%	$ 59.57
22	10	100%	$ 75.69
23	9	90%	$ 60.33
24	9	100%	$ 84.83
25	8	89%	$ 87.55
26	7	88%	$ 60.99
27	7	100%	$ 87.95
28	7	100%	$ 99.33
29	6	86%	$ 77.30
30	6	100%	$ 99.70

* For example, in the pilot study, if a customer makes two purchases, the probability that we would observe a third purchase is 80%.

Data source: Retail Relay.

Exhibit 2

RETAIL RELAY (A)

Descriptive Statistics of Customer Purchases Conditioned on How Many Times An Individual Has Ordered from Retail Relay (Full Study)

Order Number	Total Number of Observations in the Data	Conditional Probability of Observing Purchase Occasion *t + 1* in the Data if Occasion *t* is Observed	Average Dollar Amount of Purchase
1	587	NA	$ 46.71
2	322	322 ÷ 587 = 55%	$ 56.71
3	240	240 ÷ 322 = 75%	$ 57.93
4	188	78%	$ 56.87
5	156	83%	$ 58.26
6	127	81%	$ 66.90
7	103	81%	$ 63.62
8	89	86%	$ 70.27
9	73	82%	$ 63.03
10	62	85%	$ 62.60
11	56	90%	$ 71.81
12	52	93%	$ 76.76
13	44	85%	$ 78.14
14	39	89%	$ 65.65
15	33	85%	$ 74.84
16	30	91%	$ 81.11
17	29	97%	$ 72.08
18	28	97%	$ 87.30
19	27	96%	$ 71.94
20	23	85%	$ 75.44
21	19	83%	$ 70.35
22	17	89%	$ 72.86
23	14	82%	$ 66.68
24	11	79%	$ 79.90
25	9	82%	$ 93.91
26	8	89%	$ 61.08
27	7	88%	$ 94.16
28	6	86%	$ 100.40
29	4	67%	$ 77.89
30	3	75%	$ 99.70

Data source: Retail Relay.

Exhibit 3

RETAIL RELAY (A)

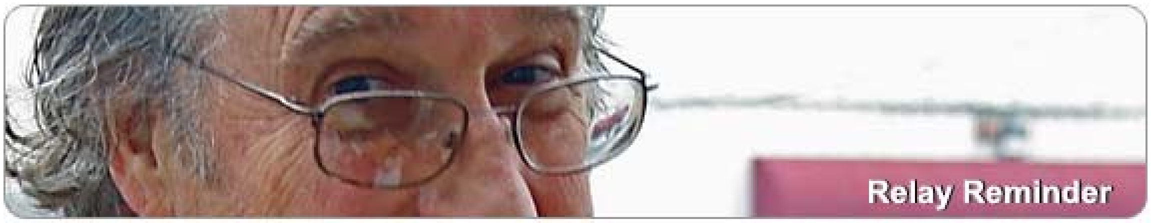
Valpak Insert

Source: Retail Relay. Used with permission.

Exhibit 4

RETAIL RELAY (A)

Sample Promotional E-mail



The Eyes of a Farmer

As Relay gears up for a great season of local food vendors, this week we roll out two new farms, each with a story to tell. The folks at Babes in the Wood refer to their pigs as **forest-fed**—which helps to explain the incredible taste of their pork products.

Likewise, writer and former technology guru, **John Kiser**, is a truly interesting soul (those are his eyes!). He began selling lean, pastured pork to his friends from Meadow Green Farm in beautiful Rappahannock County ten years ago. Try his bacon—you will realize the connection between local and *taste* in a fundamental way.

Just So You Know Dept: We've just received a new shipment from your favorite local beef provider, John Whiteside, of Wolf Creek Farm. It's all part of our spring farm market, coming soon, which will be featuring locally grown produce, cheese, and meat from our region's **Buy Fresh, Buy Local** vendors.

Thank you for your orders this week! We look forward to serving you again.

What's New:

- Babes in the Wood
- Meadow Green Farm
- Virginia Trout

Exhibit 4 (continued)

Babes in the Wood, Dillwyn, VA
From birth until the time they are taken to a USDA butcher, Babes pigs live happily unconfined in the woods. The sows even raise their young in the woods! They eat nuts and berries and root around like, well, pigs. No hormones or antibiotics. No nonsense. The result is the best quality pork available.

Meadow Green Farm, Sperryville, VA
John Kiser's Yorkshire pigs live in a luxurious 19th century barn when they're not grazing on fescue and clover-rich pasture outside. Pigs are nature's front-end loaders and theirs get their minerals directly from the iron-rich Rappahannock soil rather than antibiotic-laced corn feed. They roam, they dig, and they graze. John lets his pigs be pigs.

Virginia Trout Company, Goshen, VA
Sometimes we find our vendors, sometimes they find us. Bryan Plemmons, of **Casta Line Trout Farms** in Goshen, gave us a call and said he had trout our customers might be interested in. We listened and checked it out. One of the oldest trout farms in Virginia, Casta Line got things going in 1965 and consistently garners Blue Ribbon honors from the Virginia State Fair.

The result is Virginia Trout, which gathers the best from 5 separate Highland County trout farms—each containing pristine mountain spring water. Trout are dressed or filleted immediately upon harvesting and frozen right away to preserve their freshness. Get your Omega 3's from this delicious fish!

Source: Retail Relay.

Appendix

RETAIL RELAY (A)

Customer Lifetime Value

Customer lifetime value (CLV) can be calculated using a number of different methods. The most appropriate method is often governed by the features and restrictions of the data that is being analyzed. For a more complete discussion of methods for computing CLV see the referenced technical note on customer profitability.[1]

The data in the Excel file (UVA-M-0784X) have two important features that affect the way they should be analyzed. First, the data are organized by purchase occasion rather than by time period. Second, we can easily determine the probability that a customer who makes purchase number *t* will go on to make purchase number *t+1*. Therefore, we can also determine the probability that any new customer making his or her first purchase will continue to purchase through occasion *t*. Stated another way, these data allow us to answer questions such as "What is the probability that a new customer will make purchases from Retail Relay on at least 10 occasions?" The data set contains information on 30 potential purchase observations.

Instead of the constant retention rate found in some models of CLV, we have purchase-occasion-specific rates. The CLV expected from a new customer can therefore be calculated by **Equation 1**:

$$CLV = \sum_{t=1}^{30} \frac{r_t M_t}{(1+i)^{(t-1)}} \qquad (1)$$

where:

r_t is the probability that an individual will make purchases on at least *t* occasions given that he or she has made one purchase. For the first purchase occasion, $r_t = 1$.

M_t is the dollar contribution margin of a shopping basket at purchase occasion *t*, adjusted for distribution costs and coupon-redemption expenses.

i is the relevant discount rate between any two purchase occasions. Because the average interpurchase time in this data is about 3 weeks, the relevant discount rate can be approximated by dividing the annual rate by about 17. More accurately, the annual rate (*a*) can be converted to the 3-week rate using **Equation 2**:

$$i = (1+a)^{1/17.33} - 1. \qquad (2)$$

It should be noted that the data provided in the Excel spreadsheet do not provide the retention rate (r_t), so some (minor) data manipulation is required. Finally, while the predicted CLV might increase if we had data beyond 30 purchase occasions, 30 is sufficient to provide a reasonably accurate estimate of CLV for the purposes of this case. The case provides data for what roughly a two-year CLV (30 weeks × average interpurchase time of 3 weeks = 90 weeks).

[1] Phillip E. Pfeifer, Paul W. Farris, and Neil Bendle, "Customer Profitability," UVA-M-0718 (Charlottesville, VA: Darden Business Publishing, 2005).

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UVA-M-0809
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RETAIL RELAY (B)

In summer 2010, Retail Relay (renamed Relay Foods) expanded into Richmond, Virginia. It operated profitably for the year that followed and expected to continue to do so. During fiscal year 2011, the company more than doubled in size. In 2011, the venture capital firm Battery Ventures invested about $3 million to help Relay Foods further expand its operations. The company planned to expand into other cities.

Figure 1. Relay Foods' new logo.

Relay
RelayFoods.com

Source: Relay Foods.

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LOGISTIC REGRESSION

Almost all of us are familiar with odds. What are the chances one thing will happen versus another? What are the chances you will succeed at work today? What are the chances your favorite game-show contestant will win today versus the chances he or she will lose?

What we might not be familiar with is how odds can be applied to marketing analytics. What are the chances a customer will buy your product versus the chances he or she won't? What are the chances you will retain a customer versus the chances you will lose him or her?

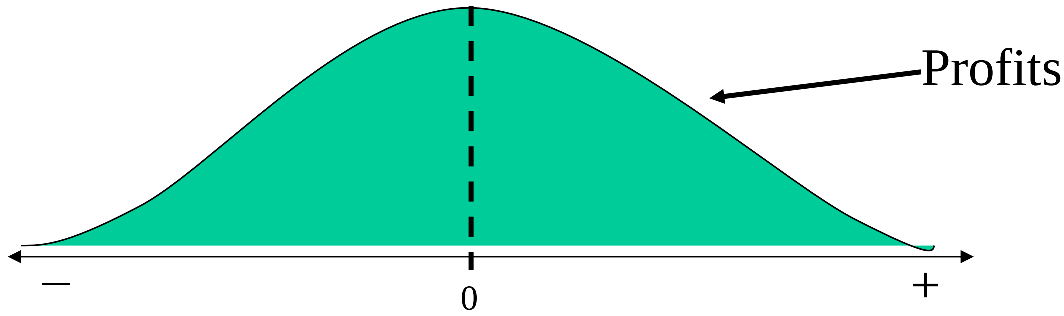
When you are using odds, you are examining two opposing outcomes. Any such unknown (i.e., one that can only be one thing or another) is known as a dummy variable. But if you know how to examine dummy variables properly, the results are anything but dumb.

When Logistic Regression Trumps Linear Regression

A logistic regression is similar to any linear regression but with one important variation that has critical consequences.

Think about an important metric in marketing: customer retention. If Keepmoney Bank wants to use a regression analysis to examine whether it will retain a customer, it will set retention as its dependent variable. Rather than being normally distributed in a bell curve in the manner of continuous variables (**Figure 1**), however, a 1 will be assigned to represent customer retention and a 0 will represent customer loss. Only those two outcomes are possible. Again, this is a dummy variable, wherein what you are trying to predict is one of two options.

Figure 1. A normal distribution.



Source: All figures created by case writer unless otherwise specified.

Studies have shown that logistic regression is the best model for examining dummy variables such as customer retention.[1] But why can't Keepmoney use its trusty linear regression to determine the likelihood of customer retention given a set of independent variables? Again, linear regressions assume a bell-curve distribution of outcomes (what is known as a normal distribution) from negative infinity to infinity. Most things in life follow this sort of distribution. Think of human height or school grades—a few people typically earn Cs, a few more earn a B−, the majority will earn Bs, and a very few will earn an A+. But when examining a dummy variable such as customer retention, there is no curve across a range of outcomes. The outcome can only be 1 or 0.

If Keepmoney attempts to use a linear regression to examine customer retention, nonsensical predictions may result. The bank may find its chances of customer retention are greater than 1, meaning it has even better than a 100% chance of retaining a customer. Or the bank may find its chances are less than 0. One can round up for those predictions that are less than 0 or round down for those greater than 1, but the results of the regression will not be precise.

Choice Behavior

The objective of logistic regression in this example is to represent consumers' choice behavior as accurately as possible. When individual consumers choose products, the value they place on the product does not typically increase linearly with increases in a preferred feature of the product. Instead, research indicates consumer valuation of a product typically follows an S-shaped curve with increases in the levels of a preferred attribute.

[1] Scott A. Neslin et al., "Defection Detection: Measuring and Understanding the Predictive Accuracy of Customer Churn Models." *Journal of Marketing Research* 43, no. 2 (2006): 204–211.

We can test whether the S-shaped curve represents consumers' choice behavior with a simple exercise. Imagine that on the x-axis we have the level of discount on a $300 plane ticket from Charlottesville, Virginia, to New York. Ask a group of your friends how many of them would purchase the flight. Then offer a discount of $20. How many additional people said they would buy the ticket? Probably not many. Increase the discount to $40. Maybe one person half-heartedly jumps in. At $60, you are likely to see a spike in purchasers. And from $60 to $100, the number of purchasers should increase at every level; however, at about $100, the number of additional purchasers will taper off, as you have reached the upper threshold.

In most real-life situations, this S-shaped curve represents how people make decisions. As a discount (i.e., promotion) increases, the odds that people will make the choice to buy will increase. In this example, at a $60 discount, 2 in 10 people are likely to purchase the flight to New York; 8 in 10 are unlikely to purchase the flight.

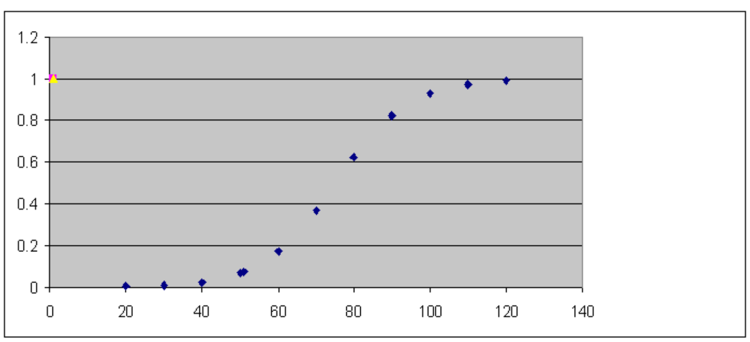
The Logistic Transformation

We now see that a linear regression would be insufficient to accurately represent individual consumers' choices. In **Figure 2**, we show a distribution of probabilities from 0 to 1 representing the logistic function

$$p\ (customer\ retention = 1) = \frac{exp(u_p)}{1+exp(u_p)}$$

where u_{p} = utility consumer obtains from product $p = a + b_1X$.

Figure 2. Distribution of probabilities for a logistic distribution.

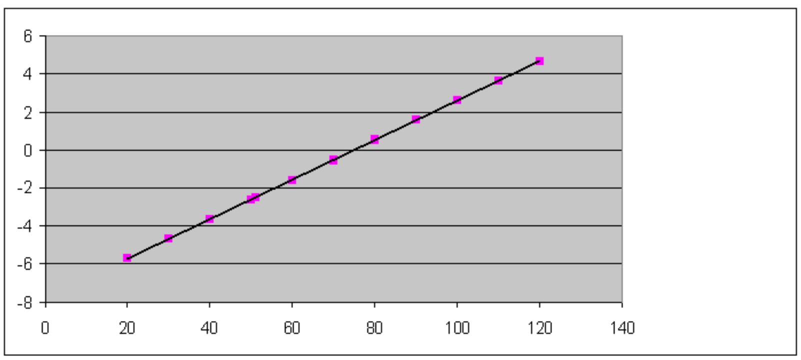


The utility function (u_p), otherwise known as a value function, is used to describe the value a person places on a certain good or service. Take coffee, for example. To find the utility, or value, you might derive from a cup of coffee, you must consider all of the variables that might go into the decision to buy that particular cup: the taste, the price, the logo, the location of the store from which you buy it, your personal habits, and the jolt it gives you in the morning. For convenience purposes—and based on behavioral studies indicating how people process variables in an additive way—the value function is assumed to be linear.

The logistic function used to describe the ways in which consumers make choices takes the form of the exponent of the value function over 1 plus the exponent of the value function. The resulting distribution looks like an S-shaped curve, as shown in **Figure 2**. The predictions from this function are bound between 0 and 1 (meaning if one outcome is 0.1, the opposite outcome is 0.9).

Furthermore, the probability of success (retention) versus failure (churn) is $P \div (1 - P)$, where P is the probability of retention. For example, if there are 10 outcomes with 1 success and 9 failures, the odds are 1/9. This ($P \div (1 - P)$) is what is known as the "odds function." Substituting for P using the logistic function above, the odds function is equal to $e^{(a+b_1X)}$. If we are to make a transformation of this exponential function to a linear function via the natural log,[2] we will find the log odds function, which is $ln[P \div (1 - P)] = a + b_1X$ (**Figure 3**). This is equivalent to the value function.

Figure 3. Log odds function.



Essentially, we have assumed a person has a linear value function or utility underlying his or her decision, then we have transformed that value into something useful about the chances he or she will make a decision. Therefore, the critical output of a logistic regression is the probability, or percent chance, a customer will stay with a company or leave the company, and that probability is defined in terms of the value the customer places on the company's product.

Assessing Video Game Purchasers

How can a marketing manager use logistic regression techniques to find useful information about the ways people behave? Consider the data in **Figure 4**, which tally the number of sales of Xbox games through Best Buy's mobile app, as reported by Kaggle.[3]

[2] See **Appendix 1** for more information on transforming an exponential function to a linear function via the natural log.

[3] Kaggle is a user-generated business analytics community. For more information, visit http://www.kaggle.com.

Figure 4. Sales of Xbox games through Best Buy's mobile app.

sku	game	numsales	abmedian	browsetime	new	regular price	customer review count	customer review average
1004622	Sniper: Ghost Warrior—Xbox 360	53	1	(0.00017)	0	19.99	7	3.4
1010544	Monopoly Streets—Xbox 360	12	1	(0.00285)	0	29.99	3	4
1011067	MySims SkyHeroes—Xbox 360	3	1	(0.00157)	0	19.99	1	2
1011491	FIFA Soccer 11—Xbox 360	85	1	(479.80822)	0	12.99	18	4.6
1011831	Hasbro Family Game Night 3—Xbox 360	6	1	0.00094	0	9.99	2	3.5
1012721	The Sims 3—Xbox 360	140	1	(0.00031)	0	19.99	13	3.8
1012876	Two Worlds II—Xbox 360	5	1	0.00047	0	39.99	8	3.4
1013666	Call of Duty: The War Collection—Xbox 360	41	1	0.00115	0	68.18	2	4.5
1014064	Castlevania: Lords of Shadow—Xbox 360	15	1	(0.00235)	0	7.99	4	4.8
1032361	Need for Speed: Hot Pursuit—Xbox 360	168	1	(0.00039)	0	19.99	45	4.2
1052221	Marvel vs. Capcom 3: Fate of Two Worlds—Xbox 360	28	1	(0.00092)	0	19.99	11	4

Data source: Kaggle, "Data Mining Hackathon on BIG DATA (7GB) Best Buy mobile web site," http://www.kaggle.com/c/acm-sf-chapter-hackathon-big (accessed November 5, 2013).

Each of the games shown in this data set boasts above-median sales compared with the other games available. In other words, a dummy variable has been set where "above-median sales" is represented by a 1, and "below-median sales" is represented by a 0. Now, which independent variables shown in the chart (time browsed, whether the game is new, price, number of reviews, and review average) are good predictors of being a 1—that is, above-median sales?

The output of a logistic regression of this data (**Figures 5** and **6**) looks similar to the output of a linear regression, and the most important data points, in addition to the coefficients, are r squared and p-value; other predictors of accuracy and significance go by a variety of names.

Figure 5. Output of logistic regression.

Summary statistics:

Variable	Categories	Frequencies	%
nrx_ind	0	1128	44.183
	1	1425	55.817

Variable	Observations	Obs. with missing data	Obs. without missing data
sales calls	2553	0	2553
Minimum	**Maximum**	**Mean**	**Std. deviation**
0.000	12.000	2.396	2.128

Goodness of fit statistics (Variable nrx_ind):

Statistic	Independent	Full
Observations	2553	2553
Sum of weights	2553.000	2553.000
DF	2552	2551
−2 Log(Likelihood)	3504.580	3216.666
R^2(McFadden)	0.000	0.082
R^2(Cox and Snell)	0.000	0.107
R^2(Nagelkerke)	0.000	0.000
AIC	3508.580	3220.666
SBC	3520.270	3232.356
Iterations	0	6

Figure 6. Model estimates.

Model parameters (Variable abmedian):

Source	Value	SE	Wald Chi-Square	Pr > Chi²
Intercept	(1.097)	0.502	4.769	0.029
New	(1.595)	1.467	1.182	0.277
Regular price	0.006	0.011	0.279	0.597
Customer review count	0.066	0.030	4.943	0.026
Customer review average	0.399	0.116	11.878	0.001

The key difference in the logistic regression output is that the coefficients are not interpreted as such. In order for the coefficients to add value to your analysis, you must calculate the odds ratio. For example, if a logistic regression yields a coefficient *b* of 2.303, the odds ratio says that for every one unit increase in the independent variable (e.g., number of promotions), the odds that the dependent variable will be equal to 1 (e.g., the product is purchased) will increase by a factor determined by taking the exponent of the coefficient: $e^b = e^{2.303} = 10$. This is not the same as a direct linear transformation.

So, examining the p-values shown in the far-right column of **Figure 6**, which variables can we say are predictive of whether a game will be a top seller? Customer review average, followed by the number of customer reviews, is the most significant variable. Price is relatively insignificant, in this case most likely due to the fact that the price range of the games is small.

Using the coefficients determined in the regression analysis, the marketing manager can then determine how much the odds of a game being a top seller increase if review average increases by one point (**Figure 7**). In other words, if a customer review average of 3 yields a certain probability of success, what happens if the average increases to 4? On average, the coefficient of customer review (coefficient *b*, the slope of the line) is 0.399, and the exponent of *b* is 1.49, which means that a single-point increase in reviews increases the odds by a factor of about 1.5.[4]

[4] For more information on how the odds ratio can be calculated, please see **Appendix 2**.

Figure 7. Equivalence of log odds ratio and logistic probabilities.

Coefficient of Customer Review Average (*b*)	0.399	
exp(*b*)	1.490	
	Customer Review Average = 3	Customer Review Average = 4
exp(*bx*)	3.310	4.933
Probability of Choice	0.768	0.831
Odds	3.310	4.933
Odds Ratio	1.490	
Difference in Probability	0.063	

For a unit increase in customer review score, the odds of selling a game increases by 49% (holding everything else constant).

$0.768 \div (1 - 0.768)$

Prob (sale) when customer review average is 3 = exp(0.399 × 3) ÷ [1 + exp(0.399 × 3)]

Prob (sale) when customer review average is 4 = exp(0.399 × 4) ÷ [1 + exp(0.399 × 4)]

Conclusion

Marketing managers often want to predict customer behaviors that are not distributed across a range of outcomes. These are cases where only one of two behaviors is possible: buy or don't buy, customer retention versus customer loss, and so on. Here, if the manager attempts to use a traditional linear regression to examine the behaviors, nonsensical predictions can result.

But a logistic regression can be used to represent consumers' choice behavior. By transforming the value function into a logistic function, we can model how the value a consumer places on a product increases with a preferred feature of the product. The critical output of the logistic regression is therefore the increase (or decrease) in the percent chance a customer will perform a behavior based on a unit increase in a variable correlated with that behavior.

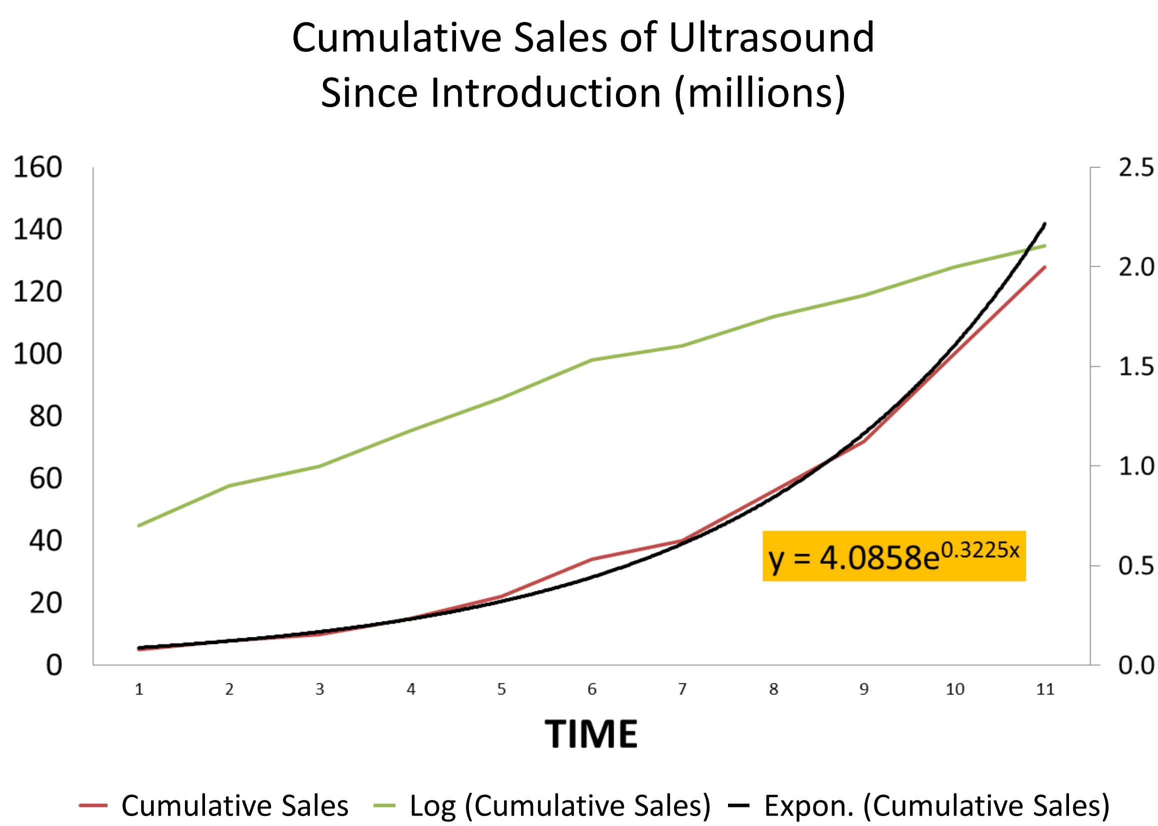
Appendix 1

LOGISTIC REGRESSION

Understanding Exponential Functions

In order to understand logistic regressions, it is helpful to first examine exponential functions. **Figure 1** shows the classic example of an exponential distribution. When considering the cumulative sales of a product that has gained market acceptance over time (such as ultrasound machines), we see that sales are slow at first but begin to increase at a greater and greater rate once they have reached critical mass. In the graph, the red line is the actual data, or number of sales per year since introduction. What stands out is that the curve is not a straight line, whereas the ones used in linear regressions are. This is an exponential distribution.

Figure 1. An example of an exponential distribution.



Source: Created by case writer.

Appendix 1 (continued)

The black line represents a function, created using a computer program,[1] which best accounts for the data shown in the graph. The regression analysis of the available data has produced a line defined by the form $y = 4.0858e^{0.3225x}$, where 4.0858 is the intercept of the line and the slope (0.3225) changes exponentially. (The constant *e* is an irrational number approximately equal to 2.71828, which is related to the rate of change in an exponential function and is the base of the natural logarithm. This function is found in a similar way as a straight-line function when performing a linear regression analysis.

One thing to note about this analysis is that the regression line fits almost perfectly. Because of the volume of data used, r squareds of up to 99% are possible, as compared with the r squareds of 20% to 30% one finds when running linear analyses. This is because the data are aggregate and viewed retrospectively, whereas linear regressions attempt to describe the behavior of individuals. If the same analysis of cumulative ultrasound sales was conducted in year two, however, it would be difficult to predict what would happen in years three, four, or five, because r squared breaks down at that point.

What does this have to do with logistic regressions? Consider the green line in **Figure 1**, which represents the natural log of cumulative sales at each time period *x*. The line is nearly straight, meaning a linear regression analysis could produce an accurate function describing the data. In other words, a logistic transformation of exponentially distributed data allows you to view the outputs of the regression in the same way you would a linear regression.[2]

[1] For more information on how to perform a logistic regression using computer software, please visit http://dmanalytics.org/.

[2] In algebraic terms, if $y = 4.0858e^{03225x}$, the natural log of *y* will equal $4.0858 + 3.225x$, a linear function where the intercept is 4.0858 and the slope is 3.225.

Appendix 2

LOGISTIC REGRESSION

Calculating Odds Ratio

Let us consider the log odds ratios presented in **Figure 7** and the logistic regression output in **Figure 6**. The log odds ratio is defined as the probability of observing an event (p) versus the probability of not observing and event ($1 - p$). In the context of the choice of games on the mobile app, we are considering the factor by which the log odds of purchasing a game increases when the review for the product increases from 3 to 4. A simple way to calculate this would be to take the exponent of the coefficient of reviews from the logistic regression output. In our case, the coefficient of reviews equals 0.399. So the log odds will increase by a factor of 1.49 or 149% (exp(0.399)) when the reviews for a product increases by one unit.

In Figure 7 we show that formula for calculating the log odds factor is equivalent to (a) computing the predicted probability of product choice when the reviews for the products are 3 and 4, and (b) then taking the ratio of these respective probabilities. The probability of product choice when average product review equal 3 is 0.768 and the corresponding log odds is 3.3. Similarly, the probability of choice when average product review equals 4 is 0.831 and the log odds is 4.933. The ratio of log odds (4.933 ÷ 3.3) equals 1.4. Hence the log odds increases by a factor of 1.4 or 140% when the average reviews for the product increases by one unit.

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RETAIL RELAY (C)

Because Retail Relay (Relay) was operating like a start-up—all employees scrambling around to get everything done in the face of rapid growth—some important business processes had been left unattended. One of the processes that received little attention was how to use the customer-level purchase information in Relay's database to improve customer retention.

Relay understood that many of its existing customers were not only spending money with Relay, but were also purchasing some of their grocery products from other vendors as well. This kind of customer behavior was evident from even a casual examination of the customer-level purchase data. Some customers purchased from Relay infrequently and sporadically, so clearly, these customers must be shopping somewhere else during the interludes between their purchases from Relay. Since customers did not sign up for a subscription plan, Relay could never be certain if a customer stopped purchasing from Relay (i.e., churned) or if they were merely dormant for a while. To overcome this challenge, Relay used a rule of thumb that classified customers as churned if their dormancy duration was more than two standard deviations above the customer's mean interpurchase timae. For example, consider a customer with a mean interpurchase time of two months, and the standard deviation in interpurchase time of three months. This customer is classified as churned if his or her dormancy duration is more than eight months.

Churned customers represented a loss of potential profit, and management believed that this loss was substantial. Yet Relay had not taken the time and energy to fully leverage its customer-level transaction data—an important customer-relationship asset—to improve customer retention. Because customers submitted their orders through Relay's website, Relay had a large and detailed database of customer orders. Among other information, when a customer placed an order, Relay knew which customer made the order, what items that customer ordered, the customer's entire order history, including the dates and times of these orders. Relay decided to use the customer-level purchase data to better understand the factors that influenced customer retention. Were there any distinct characteristics of the retained customers that could instruct Relay about how to increase the retention of its not-so-regular customers?

Relay management knew that somewhere in this data lay the key to unlocking more of its current customers' grocery dollars. Now, it needed to dig until it found that key. Would a logistic regression analysis reveal the keys to improving customer retention? To begin this process, Relay decided to explore the customer summary file described in **Exhibit 1**. To test the performance of its predictive model, Relay randomly split its customers into a "train" dataset (M-0868X2) and a "test" dataset (M-0868X1). The train dataset was used to identify the best-fitting model to predict retention. The test dataset was used to evaluate the accuracy of the predictions of the model identified in the train dataset.

This case was prepared by Ronald T. Wilcox, Ethyl Corporation Professor of Business Administration, and Rajkumar Venkatesan, Bank of America Research Professor of Business Administration. It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

Exhibit 1

RETAIL RELAY (C)

Description of Customer Summary File

Variable	***Description***
custid	Computer-generated ID to identify customers throughout the database
retained	1 if customer is assumed to be retained; 0 otherwise
created	Date when the contact was created in the database—when the customer joined
firstorder	Date when the customer placed first order
lastorder	Date when the customer placed last order
esent	Number of e-mails sent
eopenrate	Number of e-mails opened divided by number of e-mails sent
eclickrate	Number of e-mails clicked divided by number of e-mails sent
avgorder	Average order size for the customer
ordfreq	Number of orders divided by customer tenure
paperless	1 if customer subscribed for paperless communication (only online)
refill	1 if customer subscribed for automatic refill
doorstep	1 if customer subscribed for doorstep delivery
train	1 if customer is in the training database
favday	Customer's favorite delivery day
city	City where the customer resides

Data source: Company documents.

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DESIGNING MARKETING EXPERIMENTS

Introduction

In his quarterly budget presentation, Larry Culp, brand manager for BigHoney cereal, requests funds for an advertising campaign highlighting new packaging that retains freshness better and longer. In response, Mark Weinberg, BigHoney CFO, asks Culp, "Can you convince me that sales of BigHoney will be hurt if you do not advertise?" As a follow-up, he asks, "You have requested $500,000 for a national campaign? Is that the right amount? Can you get the same result for $250,000?" How can Culp convince Weinberg?

Culp's challenge is typical for marketing managers who need to invest money in the marketing mix with the expectation that sales will increase in the future. Attributing an increase in sales to a specific marketing action is a major challenge, because the effect on a brand of any single marketing activity is difficult to isolate; it consists of several levers being pulled at the same time, including price promotion, new product introductions, competitive actions, television advertising, PR events, and seasonality. Also, sales resulting from such inputs take time; a television advertisement is unlikely to compel a viewer to immediately jump off the couch, run to the store, and buy a soda. Isolating the influence of a specific event on consumer behavior can be a daunting task.

One way to isolate such influences is through experiments. In our example, Culp could, on a smaller scale, measure the effect of his proposed campaign on the brand's sales. Return on investment (ROI)—and a prospective budget—could then be estimated by projecting any identified lift to a national scale. But how does one design an experiment that would provide accurate results?

Establishing Causality

Four key rules determine a causal relationship between two variables or factors. Let us consider Culp's challenge. The marketing campaign may be considered effective if:

- Launching the marketing campaign increases BigHoney sales.
- Not launching the marketing campaign causes no change to the sales figures.
- Launching the marketing campaign today affects sales in subsequent time periods.
- There were no other established external factors (e.g., competitive action) affecting the sales of BigHoney.

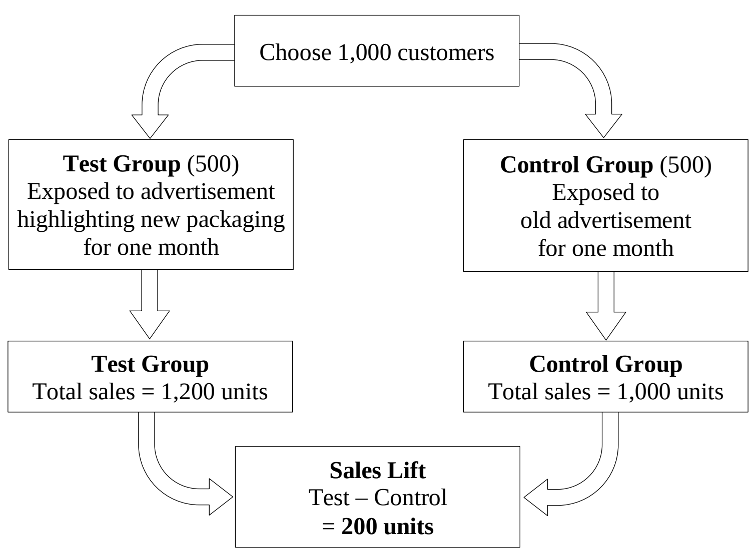
To clearly ascertain whether the targeted sales increase could be achieved without spending marketing dollars or whether any marketing spend is warranted, it becomes very important for Culp to establish causality.

After-Only Experiment

An experiment provides a mechanism to manipulate one or more input factors while controlling all other factors and observe changes in an output of interest, such as sales or brand awareness.

A very basic experiment that can be designed by Culp is illustrated in **Figure 1**. Culp recruits 1,000 participating customers, half of whom—the test group—are exposed to the *new* advertisement highlighting the new packaging technology; the other half—the control group—are exposed to the *old* advertisements. If cereal purchases by all 1,000 customers are tracked, the difference in sales between the test and control groups will indicate the magnitude of the potential sales lift provided by the new advertising campaign. Such an experimental design is called *after-only* because we measure the sales of BigHoney among the participants of the experiment only after they are exposed to the advertisement.

Figure 1. After-only experiment design.



Source: All figures created by case writer.

The after-only design satisfies two of the four conditions for causality: sales increase in the short term and in subsequent periods. It cannot indicate whether the increase might have occurred without the new advertisement, nor whether preference differences existed prior to the experiment. The underlying issue here is the extent to which the participants in the test and control groups are similar *in terms of the factors relevant to the experiment*. The more similar the factors are, the more the two pools of subjects are exposed to the same external environment—store promotions, competitive reactions, even the same weather—and then the causal inferences are more reliable, because the only difference would be the advertisement campaign to which each was exposed. Therefore, the experimenter could, with confidence, attribute a causal relationship between the marketing input and product sales.

Test and Control Group Participants

For the experimenter, deciding how to distribute customers between the test group and the control group is critical. There are two primary ways to select control groups: randomization and attribute matching. *Randomization* involves allocating participants randomly between the test group and the control group. With a big enough sample size, randomization will help improve the similarity between the test and control groups. Consider that Culp is using an e-mail advertisement campaign and has at his disposal a list of 1,000 BigHoney customers. In a random assignment, he would assign every other customer to the test group and the rest of the customers to the control group. Randomization creates fairly homogeneous test and control groups because it removes all sources of extraneous variation, which are not controllable by the experimenter. The chance that the test and control groups end up being different even with random assignment decreases as the sample size increases. For most practical marketing applications, a sample size needs to exceed at least 100 participants for a reliable random assignment process.

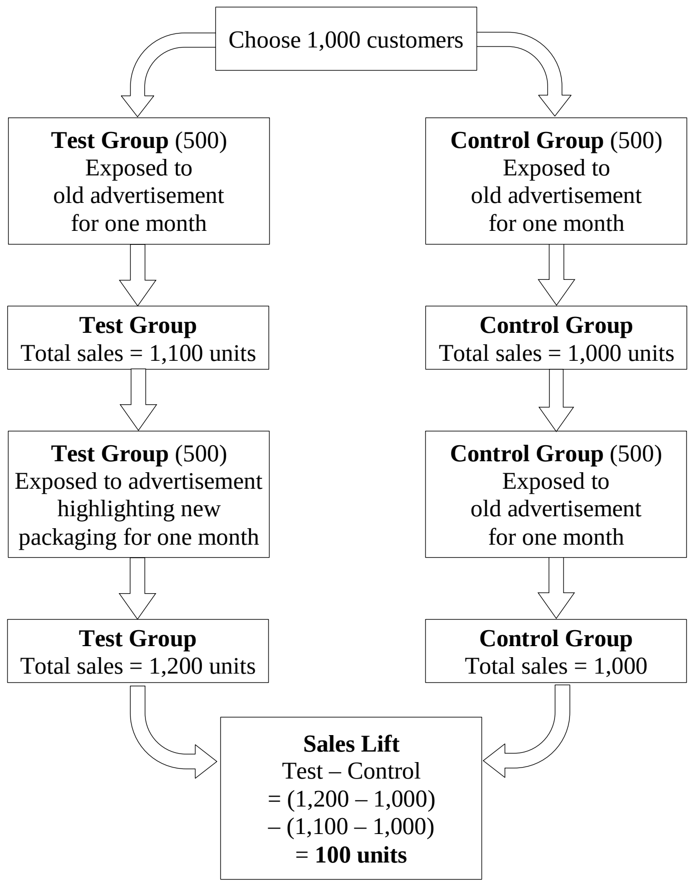
Attribute matching is used when the available sample size is not large enough to permit random assignment. Participants are assigned based on certain known attributes such as demography, geography, or annual income. If Culp were testing the effect of a TV advertisement campaign, he would be better off choosing cities that are similar in key demographic or psychographic attributes critical to BigHoney's sales.

Before-After Experiment

A *before-after* design (**Figure 2**) requires an experimenter to measure the output of interest both before and after the participants have been exposed to the inputs.

In this before-after design for an e-mail advertising campaign, Culp would randomly divide the 1,000 participants into test and control groups, as with the after-only design. Both groups would be exposed to the old advertising campaign, and sales in the respective campaigns would be recorded. Let $\Delta Sales_{before}$ be the difference in sales between the test and control groups when they are exposed to the old campaign. The test group is then exposed to the new advertising campaign, whereas the control group is still exposed to the old campaign. The difference in sales between the test and control groups now is termed $\Delta Sales_{after}$. The lift in sales due to the new advertising campaign is then calculated as $\Delta Sales = \Delta Sales_{after} - \Delta Sales_{before}$. Subtracting $\Delta Sales_{before}$ from $\Delta Sales_{after}$ allows the experimenter to control for preexisting differences between the test and control groups. This before-after design, along with random or matched assignment of participants, provides a belt-and-suspenders approach for controlling for all external differences between test and control groups.

Figure 2. Before-after experiment design.



If BigHoney cereal is sold to retailers for $1.59, and the cost of goods is 99 cents, the unit contribution equals $0.60. The lift of 100 units in the experiment translates to $60. If the cost of a single e-mail sent to a customer is $0.10, the cost of e-mails to 500 test-group customers is $50. The experiment suggests that the e-mail campaign provides an ROI of 20%. This ROI estimate can be used by Culp to plan national campaigns. Alternatively, if 500 e-mails provide $10 in contribution, the contribution from a single e-mail is $0.02. If the target lift from a national campaign is $100,000, the experiment suggests that Culp would require 5 million e-mails to attain the target lift.

Field Experiments

When experiments are conducted within a natural setting, they are termed *field experiments*. In some industries, field experiments are a part of everyday business. Retail outfits regularly use catalogs or e-mails to conduct massive field experiments that assess consumer price sensitivity and optimal catalog design. One advantage of field experiments is that subjects are seldom aware that they are part of an experiment, so the collected data is more likely to represent the realities prevalent in the marketplace. The disadvantage is that it is very difficult to control extraneous variables or to manipulate inputs precisely.

Field experiments are also very transparent to the competition, and competitive reaction could cloud the results. If, during Culp's experiment, his competition, BigSugar, launches a promotion, the results could be overly pessimistic. But field experiments are still preferred because they allow the marketer to test a campaign with customers in a natural setting, increasing the accuracy of any prediction. In general, it is easier to experiment with pricing, product, or promotion decisions than with place or channel management decisions.

If Culp also wants to determine the best price for his new packaging, he can create different test conditions where advertising, promotions, and coupons are all the same, and the only difference is price. As part of the experiment, Culp could introduce BigHoney with its new packaging in three cities (selected because they are similar in factors that affect BigHoney's sales). The only difference is that the products are priced differently in each city: $1.59, $1.89, and $2.15. The sales figures are then tracked in the three cities over time. The city where the product is priced at $1.59 could be expected to have higher sales volume—the question will be *how much* higher? The experiment results, based as before on the original cost of goods sold being 99 cents, are given in **Table 1**:

Table 1. BigHoney sales data.

	Product Price	Sales (in thousands)	Profit (in thousands)
City1	$1.59	1,000	$600
City2	$1.89	600	$540
City3	$2.15	500	$580

Given this data, Culp is better off introducing the product at the $1.59 price point, because it provides the highest profit.

Web Experiments

Because they can be executed quickly and cheaply, web experiments have gained a significant edge over traditional offline field experiments. Consider the difference between TV and e-mail advertising campaigns for Culp. With TV advertising, Culp has to buy spots in different channels in the test markets with significant lead time. Once the video is shot, it is difficult, time-consuming, and very expensive to change it. Furthermore, the cost of the experiment increases rapidly with each new version that Culp would like to test. The e-mail advertisement, on the other hand, can be created much more quickly and at a much lower cost, making it easier and less expensive for Culp to test different versions.

The faster execution and lower cost of web experiments allows marketers to easily test the simultaneous influence of multiple inputs. When Culp wants to test three different campaigns, "Lasts Longer," "Tastes Better," and the current campaign, "Good for You," each at three different price points ($1.59, $1.89, and $2.15), he can create the full factorial design shown in **Table 2**.

Table 2. Full factorial design.

	Price		
Advertisement copy	$1.59	$1.89*	$2.15
"Lasts Longer"	$1,315	$1,112	$1,206
"Tastes Better"	$957	$1,030	$1,500
"Good for You"*	$930	$820	$770

* Current conditions, therefore can be considered controls.

Each cell in **Table 2** represents a combination of advertisement copy and price point that is tested in the experiment. Since we are testing three types of copy and three price points, the total possibilities that need to be tested are 3 × 3 = 9. The profit from each combination is provided within each cell.

A TV advertisement campaign would have required Culp to recruit nine different cities for the experiment (one for each cell), as well as retailers in each city willing to manipulate the prices, a very expensive and time-consuming process. If BigHoney is sold direct to consumers through a website, then Culp can randomize the e-mails sent to consumers to match one of the nine cells in **Table 2**. The e-mail open rates, click-throughs to the website, and the subsequent purchases when consumers visit the website can be tracked for each consumer. This provides Culp with a much stronger sense of the effectiveness of the campaign because the same consumer is tracked from exposure to purchase.

The full factorial design also allows Culp to test combinations of the advertisement message and price point. In **Table 2**, we see that the "Tastes Better" message with a price point of $2.15 provides the highest profit, followed by the "Lasts Longer" campaign at the $1.59 price point. We also see that when the price is maintained at the current level of $1.89, the "Lasts Longer" campaign provides the highest profit. At least in this case, had Culp tested only the advertisement campaigns and not the different prices, he would have wrongly concluded that the "Lasts Longer" copy provided the highest profits.

Natural Experiments

In a *natural experiment*, a marketer observes the effect of certain naturally occurring incidents on customer behavior and other factors, such as sales volume. Recognizing such occurrences allows companies to learn about their customers at no or little additional expense. A classic example is Amazon collecting sales tax data from California residents. Analyzing the effect of a newly levied tax on sales volume will give Amazon an opportunity to discover how a sales tax affects online retailing. Amazon could compare sales before and after the sales tax introduction for customers who lived on either side of the state's border. The only change would be the newly introduced taxation of online purchases, which affects consumers only on one side of the border.

The most important part of identifying and analyzing natural experiments is to find test and control groups created by some external factor. Many marketers resort to geographic segmentation for natural experiments, but it will not always be a distinguishing characteristic. For example, when the Ford Motor Company introduced an employee pricing promotion, there was no natural geographic separation; all customers were offered the same deal. Instead, marketers compared sales in the weeks immediately before and after the program was introduced.

Ford Motor Company discovered that the jump in sales levels was accompanied by a sharp increase in prices. Customers presumed that they were getting a good deal, but the prices on many models were actually lower before the promotion than at the time of the employee discount prices. But customers responded to the promotion *despite* the prices, not *because* of the prices. The program led to many happy customers, even though they were paying higher prices.

Challenges

The accuracy of data obtained from a marketing experiment increases with the experiment's duration. For example, experiments that have shorter durations might not adequately account for the carry-over effects of marketing interventions; however, marketing decisions are mostly sensitive to time, highlighting the tension between quick versus accurate decisions. The longer the gap between the field experiment and the full campaign, the less accurate the prediction from the field experiment. Yet the time required to obtain buy-in for the field experiment results could delay the timing of the full campaign and thereby the relevance of the field experiment. If an experiment involves salespeople, the mere knowledge of being in an experiment could change their behavior (the *demand effect*), leading to biased conclusions.

Experiments provide a bridge between new ideas and management decisions. Digital marketing has popularized experimentation in the marketing community. Organizations can succeed if they develop a system to learn from experiments and strive toward continuous improvement.

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TRANSFORMATION OF MARKETING AT THE OHIO ART COMPANY (A)

Ohio Art Company History

The Ohio Art Company—among America's oldest toymakers—was headquartered in Bryan, Ohio, a small town in the northwest part of the state. Although Ohio Art made over 50 toy varieties including dolls and water toys, its flagship product was a drawing toy it had been selling for more than 52 years: the Etch A Sketch (EAS®). In that time, over 100 million units had been sold to consumers in dozens of countries. Ohio Art's slogan, "Making Creativity Fun," demonstrated the company's commitment to arts and crafts products. Although most of its sales came from its toy business, Ohio Art also produced and sold custom metal lithography, which contributed one-third of the company's revenues and a disproportionate share of profits.[1] In recent years, Ohio Art's toy business had experienced a bumpy ride, alternating between profits and losses throughout the 1990s and up through 2011. Product placement of EAS in the hit animated movie *Toy Story* was a shot in the arm for Ohio Art in 1995. In 1998, the company introduced a new doll called Betty Spaghetty, which was an initial hit with consumers, but its popularity and sales had waned over time. "Aimed at girls ages four and up, the small doll featured interchangeable limbs, spaghetti-like hair, and a variety of accessories, such as a cell phone, a laptop computer, and in-line skates."[2]

Toy Supply Chain and Seasonality

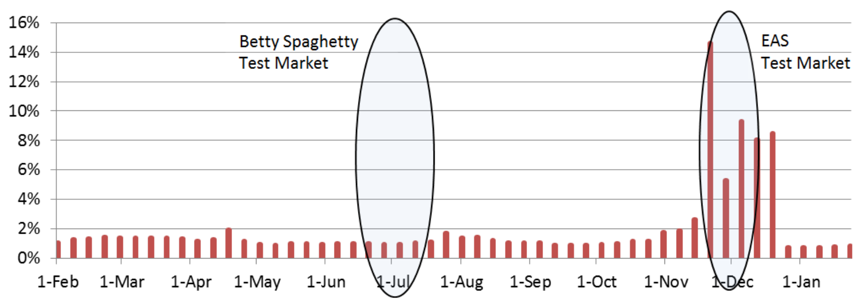
Toy retailing had become more concentrated, with Wal-Mart, Toys"R"Us, and Target accounting for the overwhelming majority of sales.[3] The need for lower costs (to compete effectively in the mass-merchant channel) forced Ohio Art to shift all production of its toys to

[1] "The Ohio Art Company," *International Directory of Company Histories*, vol. 59 (St. James Press, 2004).
[2] "The Ohio Art Company History," http://www.fundinguniverse.com/company-histories/the-ohio-art-company-history/ (accessed Jun. 8, 2012).
[3] Wal-Mart had the highest market share at about 25%, followed by Toys"R"Us at 17%, and Target at 12%.

China in 2001. Making an EAS in China and delivering it to the warehouse in Bryan, Ohio, cost the company 20% to 30% less than making it on-site.[4] The shift in production to Asia magnified the already high risks of introducing new products. Long shipping times and the seasonality of most toy sales meant that inventory management and tooling risks were significant. In 1998, a "'major retailer' abruptly canceled a $15.2 million toy order just before the holiday season. [Ohio Art] was left with a large amount of excess inventory and also was unable to cancel television advertising commitments that had been made in support of the holiday line."[5] Fortunately, in 1999, the company was again helped by the release of *Toy Story 2*, which featured a 30-second spot showing the Etch A Sketch. Management attributed the 20% increase in holiday EAS sales to that exposure.

The company's fiscal year ended January 31; November and December typically accounted for 45% of retail sales. Each of the other 10 months averaged close to 5.5% (see **Figure 1**). This same pattern was typical for almost all toys, including Ohio Art's.

Figure 1. Ohio Art toy seasonality.



Data source: Ohio Art. Used with permission.

The Etch A Sketch Experiment

Although the EAS line had been promoted initially with heavy television advertising, by late 2006, advertising budgets for the EAS were below $1 million, most of which went toward reimbursing retailers for cooperative advertising. Too often these funds did little more than fund temporary price reductions. No national television advertising had been done for several years. In late 2006, however, the company's advertising agency proposed a new campaign to enhance the toy's continued popularity. In part, this was due to a recent request by Target to include the EAS in its own television spot.

Although management was divided on whether an advertising campaign would be economical, it was decided to test the effectiveness of renewed television advertising through a field experiment that lasted from November 27 to December 16, 2006, a three-week period

[4] Joseph Kahn, "Ruse in Toyland: Chinese Workers' Hidden Woe," *New York Times*, December 7, 2003.
[5] http://www.fundinguniverse.com/company-histories/the-ohio-art-company-history/.

during which approximately 35% of retail toy sales normally occurred. Management intended to assess the results by comparing the test and control market sales of its largest retail customer (25% sales). This retailer had retail stores in all control markets and POS systems that allowed accurate monitoring of sales. The expectation was that observed sales increases would accrue to all retailers. Sales data from the previous year were not available because the merchant had removed EAS from its shelves for much of the year due to a pricing disagreement. The resolution of that disagreement had put EAS back on the shelves, and some of the management team thought that a sales boost through advertising would be a timely move to restore good relations between Ohio Arts and the retailer.

Television commercials for the EAS were aired during syndicated morning and evening talk shows, daytime soaps, and evening news programs only in Cincinnati, Ohio, during the three test weeks. There were internal concerns that Cincinnati might not be a good test market, since it was in the same state as the company's headquarters. But research showed that not only was company location not a concern for buyers, but an overwhelming majority of consumers didn't even know that EAS was made and marketed by an Ohio company. Commercials were not aired in any other place in the United States during the test period. The breakdown of the total advertising spend in the three weeks is provided in **Table 1**. The cost of working with an outside agency to develop the test EAS commercials was $75,000. The media spend called for more than 100 spots, each with an average rating of 2.7 to be broadcast over the three weeks.[6] The $30,150 media spend in Cincinnati would be equivalent to a $5 million national budget. Total annual unit sales of the EAS products were 3.1 million before the test.

Table 1. Media spend in Cincinnati.

Dates	**Total Cost**	**Total Rating Points**	**Number of TV Spots**
Nov. 27–Dec. 1	$ 9,350	91.8	39
Dec. 2–Dec. 8	$10,200	106.3	44
Dec. 11–Dec. 16	$10,600	112.1	46
Total	***$30,150***	***310.2***	***129***

Data source: Ohio Art. Used with permission.

Four other cities—Charleston, South Carolina; Cleveland, Ohio; Indianapolis, Indiana; and Pittsburgh, Pennsylvania—were chosen as controls to evaluate whether the EAS advertising led to increased sales (see **Table 2** for city demographics). In choosing test market cities, several factors should generally be considered. First, the test city (or cities) must reflect market conditions in the product's market area, whether it was local, regional, national, or global. No city could represent all market conditions perfectly, and success in one city did not guarantee success elsewhere. Typical criteria for good test markets included similarity to planned distribution outlets: representative population size, demographics, income, purchasing habits, and freedom from atypical competitive activity.[7]

[6] One rating point was equal to 1% of the total population in a given area.
[7] Charles W. Lamb, Joseph F. Hair, Carl D. McDaniel, and Daniel L. Wardlow, *Essentials of Marketing*. (Cincinnati, OH: South-Western College Pub., 1999).

Table 2. Test and control city demographics.

	Cincinnati	Charleston	Cleveland	Indianapolis	Pittsburgh
Median age	36	33	33	34	36
Median income (family)	$37,543	$47,942	$30,286	$48,979	$38,795
Average family size	3.05	2.39	3.19	3.03	2.95

Data source: Ohio Art. Used with permission.

The greater Cincinnati area represented about 0.7% of the U.S. population. The average population of the control cities was around 2 million, which represented about 0.6% of the U.S. population. See **Table 3** for sales data for EAS and another new Ohio Art product, Doodle Doug, in Cincinnati and the four control cities at selected stores of the major mass merchant.[8] Doodle Doug was not advertised, but sales were tracked in the cities as an additional control in interpreting the results.

Table 3. EAS and Doodle Doug weekly unit sales in test and control cities (1/1/05–2/2/07).

Dates	CINN EAS	Control Cities EAS	Total Chain-Wide EAS	Advertising Spending	CINN Doodle	Control Cities Doodle
Jan 1 - Sep 1 Average	11.2	79.1	1,396.6	No	101.3	440.4
Jan 1 - Sep 1 Std Dev	5.4	27.3	319.4	No	29.8	120.8
Sep 2-8	12	103	1,242	No	82	333
Sep 9-15	12	71	1,130	No	71	317
Sep 16-22	10	87	1,184	No	52	280
Sep 23-29	9	79	1,213	No	68	279
Sep 30-Oct 6	10	96	1,178	No	58	248
Oct 7-13	9	121	1,327	No	72	329
Oct 14-20	14	101	1,349	No	95	331
Oct 21-27	10	116	1,438	No	96	362
Oct 28-Nov 3	11	118	1,582	No	201	651
Nov 4-10	15	134	1,878	No	204	1,187
Nov 11-17	24	214	2,597	No	277	1,325
Nov 18-24	26	286	3,844	No	241	1,100
Subtotal for Period	162	1,526	19,962	No	1,517	6,742
Nov 25-Dec 1	61	370	4,604	Yes	217	926
Dec 2-8	70	488	6,959	Yes	249	1,211
Dec 9-15	109	740	9,867	Yes	347	1,643
Subtotal for Period	240	1,598	21,430	Yes	813	3,780
Dec 16-22	145	971	12,845	No	346	2,207
Dec 23-29	39	312	4,298	No	157	1,009
Dec 30-Jan 5	1	46	1,137	No	100	296
Jan 6-12	12	62	1,137	No	80	310
Jan 13-19	15	86	1,412	No	136	318
Jan 20-26	23	65	1,424	No	83	297
Jan 27-Feb 2	10	77	1,522	No	122	332
Subtotal for Period	245	1,619	23,775	No	1,024	4,769

Data source: Ohio Art. Used with permission.

[8] Unit sales figures are not provided in some weeks because EAS was not carried by the mass merchant in these weeks due to disagreements over price points.

One Ohio Art executive worried that the test would be difficult to read and suggested that a split-cable test could be implemented in April of the following year for about $500,000.[9] He believed the estimate of the projected sales lift from such a split-cable test would be much more accurate.

The suggested retail price for EAS was $12.99. The Travel, Pocket, and Mini Etch A Sketch were less expensive at $8.99, $4.99, and $2.99, respectively. Given unit sales for each product, the weighted average of all EAS products sold in the holiday time period was $10.00. It was this $10.00 price that was suggested for use in calculating the percentage increase required for a national campaign. The suggested retail price for Doodle Doug was $14.99. The company's average gross margin for the EAS products was 58%, and the average retail margin was 36%. (See **Figure 2** for pictures of the EAS and Doodle Doug.)

Figure 2. EAS and Doodle Doug toys.

Source: Ohio Art. Used with permission.

The Betty Spaghetty Experiment

In mid-2007, the company implemented another field experiment for a revamped Betty Spaghetty product line. The test had three objectives: (1) estimating consumer demand for the revised Betty Spaghetty line, (2) testing whether advertising could increase sales (and profits) obtained for the redesigned Betty Spaghetty, and (3) convincing the merchandise manager at a mass-merchant chain that those sales of Betty Spaghetty would justify the allocation of shelf space. For the Betty Spaghetty experiment, television and radio commercials were aired in Arizona for four weeks from June 17, 2007, to July 14, 2007. The company purchased 600 gross rating points (GRPs) for the television advertisements for a total cost of $31,500. The ads were aimed at girls between the ages of 2 and 11 and were aired on local cable channels, such as Nickelodeon and the Cartoon Network. Management also purchased 64 GRPs for radio

[9] Split-cable testing systems allow for delivery of separate advertising campaigns or a different level of advertising exposures to different groups of households within a given market and tracked purchases through consumer diaries or other panel data. This eliminated differences in retail environments, competitive activity, and other market characteristics among test and control groups.

commercials for a total cost of $8,022. The radio commercials were aired during morning and evening commutes. Each of the television and radio programs selected for the commercials reached about 1.8% of the population in Phoenix. The cost of developing the commercial through an outside agency was $150,000.

Management estimated that an equivalent ad budget for eight to ten weeks of preholiday advertising, factoring in certain economies as well as the higher seasonal cost of media, would be approximately $3 million. The average retail selling price of Betty Spaghetty during the test was about $15.00. Retailer and Ohio Art margins were about the same as for EAS, 36% and 58%, respectively. Given that some time would be required to read the test, obtain shelf space, and ship product to stores, management estimated that the four-week test market sales period represented about 10% of the total remaining sales potential for the year.

Table 4 reports weekly sales in 23 Arizona stores (test) and in 24 stores of the same mass merchant in California (control) for two versions of Betty Spaghetty. The stores represented 50% of the retailer's Arizona sales and 10% of California sales, respectively. Arizona and California represented 2% and 12%, respectively, of the retailer's national sales, and that same retailer was expected to account for 25% of total Betty Spaghetty sales. Management intended to use the test to help estimate Betty Spaghetty sales with and without advertising.

Table 4. Weekly unit sales of Betty Spaghetty in test and control cities.

	Color Crazy Test (AZ)	Go-Go Glam Test (AZ)	Color Crazy Control (CA)	Go-Go Glam Control (CA)
Week 1	30	56	1	12
Week 2	28	59	5	18
Week 3	51	51	7	36
Week 4	54	40	17	46
Total	163	206	30	112
Total/store/week	1.8	2.2	0.3	1.2

Data source: Ohio Art. Used with permission.

TRANSFORMATION OF MARKETING AT THE OHIO ART COMPANY (B)

Introduction

In March 2012, the Ohio Art Company, best known as the manufacturer and marketer of the classic toy, Etch A Sketch (EAS), had been distracted from its efforts to shift its marketing emphasis from traditional mass-marketing channels to more targeted digital marketing. Management believed such a shift would be necessary for the company to thrive in the next decade. The distraction came from the media attention surrounding recent comments made by a campaign manager of Republican presidential candidate Mitt Romney. Having been thrust into the middle of a political controversy, Ohio Art needed to decide how (and whether) to react to the growing media attention.

Distraction or Opportunity?

When asked how a campaign might change tactics from primary to general elections, Romney's adviser Eric Fehrnstrom replied, "You hit a reset button for the fall campaign. Everything changes. It's almost like an Etch a Sketch. You can kind of shake it up, and we start all over again."[1] The result was a media firestorm. Ohio Art received numerous calls from the media, and management knew it had to decide on a plan.

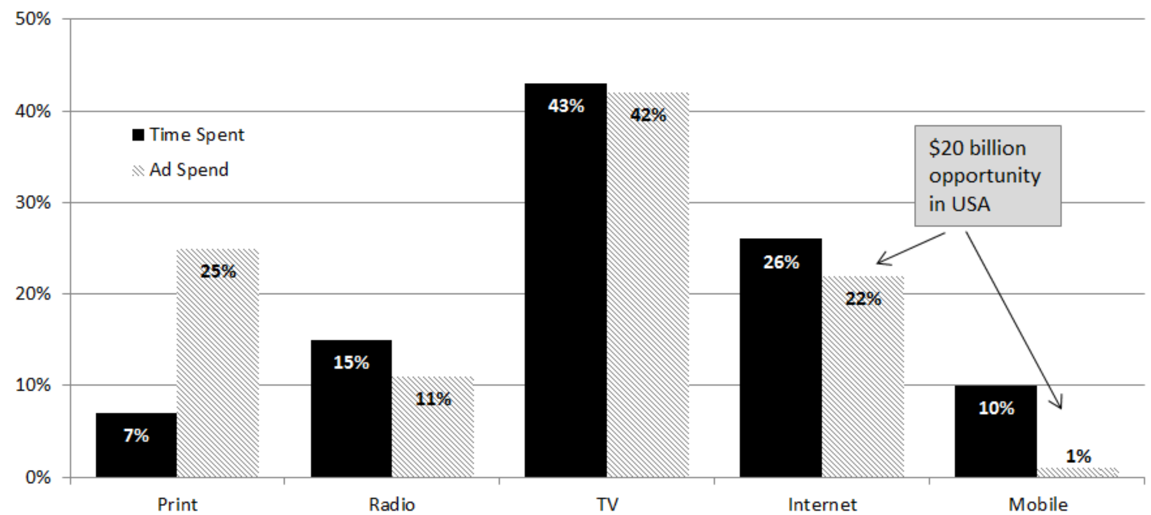
Management was concerned that investing time and financial resources to leverage the media attention might take resources away from the company's new star product—nanoblock construction toys. Because it appealed to a wide range of ages, it would be a great candidate for promotion through digital media. For both nanoblock and the traditional EAS line, digital and

[1] Sam Stein, "Mitt Romney Platform 'Like an Etch A Sketch,' Top Spokesman Says," *Huffington Post*, March 21, 2012, http://www.huffingtonpost.com/2012/03/21/mitt-romney-etch-a-sketch_n_1369769.html (accessed Jul. 23, 2012).

This case was prepared by Paul W. Farris, Landmark Communications Professor of Business Administration; Meghan Murray, Instructor; and Rajkumar Venkatesan, Bank of America Research Associate Professor of Business Administration, with the assistance of Dustin Moon (MBA '12). It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

social media and online retailers offered opportunities Ohio Art had yet to explore. **Figure 1** suggests that there was significant room for further growth in both Internet and mobile advertising due to the gap between the percentage of time consumers spent with Internet and mobile devices and the percentage of dollars advertisers devoted to these media.

Figure 1. Percentage of time spent using media versus percentage of advertising spend, 2011.



Data source: Adapted from Mary Meeker, "Internet Trends," Kleiner Perkins Caufield Byers presentation transcript, D10 Conference, May 30, 2012, 17, http://www.scribd.com/doc/95259089/KPCB-Internet-Trends-2012 (accessed Jul. 26, 2012).

In addition to the Internet search and display ads, there were rapidly emerging opportunities to promote through Amazon.com and social media. Social media was particularly intriguing because management thought that outlet might offer new revenue models for the EAS brand. Up until this point, the EAS brand had been mainly leveraged through an increasing number of product variants, and the productivity of introducing more EAS product extensions seemed limited. Over 150 million EAS-related products had been sold by mid-2012.

Figure 2. The EAS product and select variants.

Source: Ohio Art. Used with permission.

Martin Killgallon, Ohio Art's VP of marketing, thought he could capitalize on the iconic nature of the brand by exploring partnership opportunities with other marketers. For example, the company had licensed iPhone and iPad covers that gave those devices the appearance of the EAS. iPad and iPhone mobile applications also mimicked the action of the EAS on the iPad and iPhone screens. These EAS apps, offered through Apple, Amazon, Google, and Barnes & Noble, had over 1.3 million downloads between mid-2010 and mid-2012. And interest in the timeless toy did not seem to be slowing down. In May 2012, a California start-up company created an accessory called "Etcher" as part of a project with Ohio Art: an iPad case styled after the EAS. It consisted of a bright-red plastic case with two familiar-looking knobs that were used for drawing horizontal and vertical lines. The system interfaced with an iOS app that replicated the toy's drawing experience. The iPad version allowed users to save and share their work with others on social networks or simply shake the screen to erase their creation and start over.

The company typically negotiated a royalty payment of 5% to 10% of gross revenue for licensed products such as this. The image of the EAS product was also often used in advertising as a prop, conveying fun and creativity in the context. Sometimes Ohio Art paid to be included (e.g., Target holiday commercials), and sometimes the company granted permission in return for expected favorable exposures (e.g., ESPN and BMW Mini commercials). Management thought there was more the company could do to capitalize on the high brand recognition and nostalgia associated with the EAS product, but it was unsure exactly what to do and how it might be monetized.

A Shift in Strategy

Ohio Art made shifts in all aspects of its marketing mix in reaction to developments in the toy industry and the growth of online retailing. Management believed these shifts were investments that would make Ohio Art a stronger competitor in the upcoming years.

Product

Instead of designing toys from the ground up and investing in its own tooling, Ohio Art began looking to license toys for exclusive distribution that were developed by other international toy companies or smaller entrepreneurial toy companies that were trying to gain access to stronger distribution and marketing capabilities. With this approach, focusing on new channels and monitoring marketing investments, the company believed it could reduce the risk of introducing new products. Early signs were that the strategy was working at least with its new nanoblock product, which seemed to have a lot of potential. Other licensed products included K's Kids (infant and toddler toys) and Clics (construction) for younger children and Air Picks (an "air guitar" toy that played famous guitar riffs) for preteens and older kids.[2]

[2] See the Ohio Art website for a complete listing of individual products: http://www.world-of-toys.com/category_s/58.htm (accessed Jul. 30, 2012).

Channels

The traditional line of products (EAS and Doodlesketch) was stocked by the three largest toy retailers—Wal-Mart, Target, and Toys“R”Us—as well as a number of other mass and discount retailers, including dollar stores and drug stores. For the new line of licensed products, including nanoblock, the company was shifting to specialty toy stores, plus Toys“R”Us and a few bookstores, such as Barnes & Noble and Amazon.com. Management believed that attempting to distribute the new products through mass merchandisers would reduce the enthusiasm of the specialty channels (including Toys“R”Us) to stock and promote these items. Also, broadening the distribution channels would make the company less vulnerable to sudden changes in stocking, merchandising, and promotion decisions by individual retail chains. By mid-2012, approximately 1,100 accounts stocked at least some of the nanoblock line. Of those, most were specialty toy retailers or accounts such as Urban Outfitters or Barnes & Noble, which also sold hobbies and toys. Toys“R”Us and Amazon were expected to account for 65% of nanoblock units sold in 2012.

Pricing, discounts, and margins

One of the reasons for moving to new channels was an attempt to escape the relentless price pressure, “unauthorized deductions,” and promotional allowances required by large retailers. Specialty toy retailers tended to price products to earn 50% margins. These independent toy retailers were serviced by manufacturer representatives who typically earned commissions of 10% for sales to specialty stores. Mass retailer margins were lower. For a heavily promoted item, they were 35% or so, and for Ohio Art products, they were closer to 45%. Manufacturer representative commissions to this channel were lower: 4% to 5%. Ohio Art was determined that the new product line would not be subject to the same price pressure as the traditional line and intended to discontinue retailers that did not respect the suggested retail price levels.

Marketing communications

Historically, sales of the core EAS line had increased in response to such publicity as the featured role in the movie *Toy Story*, but the gains had been short-lived and might have been due to retailer reactions—more displays, better shelf space, fewer out-of-stocks, and the like—as much as consumer demand. Finding efficient ways to promote the line of Ohio Art toys was an ongoing challenge. Traditional marketing channels were not growing sales of EAS, and the nanoblock line was an impetus to try new strategies.

Nanoblock History

Developed and manufactured by Kawada and first sold in Japan in October 2008, nanoblock allowed users to build detailed, intricate models because of their tiny size. The blocks, which were about one-eighth the size of other popular building bricks, were made from high-quality ABS plastic and featured a double-ridged backing that enabled the tiny pieces to fit together almost seamlessly. They appealed to various age groups because of the variety of building sets offered (**Figure 2**).

Because of the blocks' instant popularity in Japan, large Japanese retail chains had dedicated much shelf display space to nanoblock. In addition to its regular lineup of products, Kawada also offered licensed products and special-edition products. The company also regularly added new items to its catalog, sometimes based on user-submitted ideas.

Figure 2. Sample nanoblock sets (suggested retail prices \$9.99, \$12.99, \$19.99, and \$164.99).

Source: Ohio Art. Used with permission.

In late 2011, Ohio Art conducted an online survey to evaluate the demographics of its core customers. The survey revealed that almost 90% of its purchasers were between 25 and 54 years of age.[3] With this valuable information about buyers, Ohio Art could now make informed decisions about marketing dollars for nanoblock. Specifically, Amazon aimed to use data, technology, and expertise to put the most appropriate products in front of the most qualified and receptive potential buyers. Amazon had built proprietary merchandising technology that allowed it to present a fully customized store to every consumer who visited its website. Companies selling on Amazon benefitted from Amazon's commitment to drive sales by putting the right products in front of the right customers.

A study of online shopping behavior reported that Amazon.com was the source used most frequently for product reviews and ratings. Amazon was used by 58% of respondents, compared with 45% for other retailers (e.g., Wal-Mart, Best Buy), 41% for search engines (e.g., Google, Bing), 32% for manufacturers' websites (e.g., Nike, Lego), 25% for review sites (e.g., Epinions, CNet), 11% for Facebook, and 7% for Twitter.[4]

[3] Christopher Tan is a self-proclaimed "nanoblock enthusiast" from Malaysia. He wrote a blog specifically dedicated to the product. See his post "Why nanoblock is Cool!" September 21, 2011, http://www.inanoblock.com/2011/09/why-nanoblock-is-cool.html (accessed Jul. 30, 2012) to understand more about the product and what types of consumers were interested in it.

[4] "The 2011 Social Shopping Study," *Power Reviews*, June 2011, p. 14, http://www.powerreviews.com/assets/download/Social_Shopping_2011_Brief1.pdf (accessed Jul. 24, 2012).

Amazon also offered a variety of targeted advertising options (see **Table 1** for a description of the typical merchant services offered by Amazon.com) with rates that generally doubled for the toy category in the last quarter of 2011.

Table 1. Merchant services offered by Amazon.com in 2011.

Name	**Description**	**Rate***
Automated and personalized merchandising	Dynamically recommended products relevant to customers' current search and browsing behavior.	Free
Community gifting	Customers could create and share wish lists and gift registries.	Free (featured in a customer's wish list or gift registry)
Social media	Featured in Amazon's toy blog, and Facebook and Twitter feeds.	Free
Promotional site placement	Featured product on different parts of the main promotional site.	$7,500 to $2,000 per week for the main promotional site. Rates were highest for the center stage, followed by the right rotations, the logos at the bottom, and finally the banner at the top of the site. Advertisements were featured 20% to 50% of the time.
Product detail page display	Better product details and descriptions on the product page.	$1,400 one-time fee.
Product page promotion	Placed promotions on the product page.	$5,000 per week. Promotions were featured 25% of the time.
Amazon Vine	Select group of customers posted opinions about new and prerelease items.	$2,500 one-time fee per product.
E-mail outreach	Featured in Amazon's targeted promotional campaigns.	$12,000 per year for auto e-mail program. $0.15/mail for a single targeted campaign.
Search results	Advertisement featured on top of customer's relevant search results.	$1,500 per month.
Brand store	Customized, single, central destination for all the firm's brands and products.	$50,000 per year for cross-category store and $35,000 per year for a toy category store.
Gateway placement	Placement on Amazon's landing page.	$65,000 to $32,000 per week, with higher rates for center placements, followed by right and then bottom. Ads were featured 10% of the time.

* Rates are for Q1–Q3. Q4 rates are higher. Services can be customized for a specific merchant. The customized rates are not included here.

Data source: Amazon.com.

According to Larry Culp, an Ohio Art sales rep, the company had always had a consistent presence on Amazon due to the EAS products. But the company had not done much to promote new products on Amazon until the debut of nanoblock. Amazon, like many technology-driven sites, used algorithms and collaborative filtering to determine search results' relevance. *Collaborative filtering* was a process used to generate product recommendations by matching the purchase histories of many different users. Without a minimum purchase volume, these recommendation algorithms did not have enough history to generate relevant recommendations for nanoblock.

One way the company was able to increase the potential for relevant recommendations was through Amazon's "Gold Box" promotion, where items were offered at reduced prices for an hour or two on a given day. Ohio Art decided to fund a promotion for its Eiffel Tower nanoblock set in the "Lightning Deals" section of Gold Box on March 4, 2012 (see **Table 2** for sales data on select products). Companies paid Amazon to promote their products this way; fees were determined by the number of units companies made available for the deal multiplied by the discount (versus Amazon's normal price). In this way, companies were challenged to forecast properly; an overestimation would result in higher promotional costs while an underestimation would result in foregone sales. These "Lightning Deals" increased the number of user clicks on the nanoblock product, thereby increasing the relevance of Ohio Art and nanoblock. That, in turn, increased the number of appearances for Ohio Art's products even after the promotion ended. Ohio Art sold all 300 Eiffel Tower sets it offered at $12.99 in the Lightning Deal. The rest of March volume was sold at the regular $19.99 price.

Table 2. Sales data on selected products.

Ohio Art Product	Sales Price	Jan–Feb 2012	March 2012	May 2012
nanoblock Eiffel Tower	$19.99	274	686	219
nanoblock Taj Mahal	$19.99	308	163	132
nanoblock Castle Neuschwanstein	$19.99	244	184	146
Classic EAS	$12.99	344	352	399

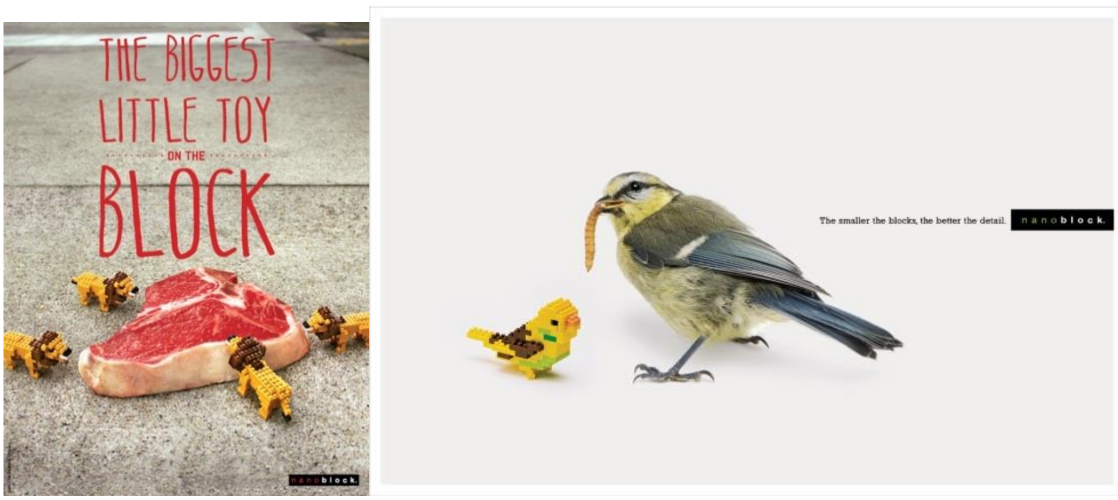
Finally, Amazon charged suppliers a 10% cooperative advertising fee. This fee was justified by Amazon providing search capabilities and using Google AdWords/Microsoft AdCenter to get top results in searches for merchants' products. For example, the top advertised spot in a Google search for "nanoblocks" was the Amazon.com link to Ohio Art's products. Ohio Art was trying to determine if Amazon was a great new channel or if the challenges associated with it would be just as tricky as those it faced in dealing with traditional retailers.

Opportunities

EAS sales were stagnant, but nanoblock sales were growing. The targeted-audience data about nanoblock's customers coupled with a taste of Amazon's variable pricing motivated management to consider engaging in other new media. Ohio Art's ad agency recommended advertising that was playful and sophisticated for the adult audience. And the Amazon sales empowered management to recognize that it could push for positive return on investment rather than financing a large traditional ad campaign and then sitting around hoping for results. The new model of testing several tactics, discontinuing the ones that did not work, and honing the definitive successes was much more appealing—for all products, not just nanoblock.

Ohio Art utilized its Facebook.com/EAS page primarily for polls and factoids. Posts ranged from “Fun Fact: World’s Largest #EtchASketch weighs 300lbs” to “Does this expertly sketched Mona Lisa make you smile or pout?” These efforts earned it over 7,000 fans by mid-2012. For the nanoblock Facebook page, Ohio Art produced a series of targeted poster ads, special offers, and announcements about fun things that were going on. With nanoblock in particular, the company attempted to create a forum for fans to communicate with each other, asking questions and sharing creations. The videos were quite popular on the nanoblock USA Facebook page, resulting in over 3,000 fans by mid-2012.

Figure 4. Targeted nanoblock poster ads, spring 2012.[5]



Source: Ohio Art. Used with permission.

There were several ways that companies could use blogs to promote their products. In 2010, Google Blogger introduced BlogSense accounts. Companies would pay for advertising on blogs that Google determined were related to their products. A percentage of the proceeds would go to the blogger. Of particular interest to Ohio Art was the fact that “Mommy Bloggers” had recently become very popular. Top Mommy Bloggers had thousands of daily visitors to their sites, many of whom were avid, loyal readers who deeply valued the writer’s opinions. Companies could create incentives for these bloggers to promote or review their products on their blogs, which Ohio Art pursued in 2010 and 2011. The venture resulted in over 350 websites creating permanent links to the Ohio Art sites—http://www.world-of-toys.com/ (the retail website) and www.OhioArt.com. By mid-2012, the company was evaluating whether to attempt to convert certain Mommy Bloggers into affiliates. Affiliates would link to Ohio Art’s website and receive commissions on sales that resulted from those click-throughs. Company-sponsored events, such as luncheons to demonstrate new products, functioned as forums to inform and entertain 20 or so bloggers at a time. The success of these small events was one argument for

[5] See the Facebook page for examples of video and poster ads created by the company advertising agency: https://www.facebook.com/nanoblockUSA.

considering larger events (e.g., inviting 350 bloggers to events sponsored by third parties or sponsoring booths at blogger conventions).

Ohio Art had also developed an interest in Pinterest, a content-sharing website where users could create, manage, and share theme-based "pinboards." Users could browse other users' pinboards, follow other pinners, and repin images to their own collections. Pinterest allowed users to share their pins on Twitter and Facebook, and with more than 12 million users (more than 80% female), it was the fastest social media site in history to break 10 million unique visitors.[6] Users typically pinned things such as recipes, décor, children's toys, and do-it-yourself crafts. But by the middle of 2012, Pinterest had not yet been explored by Ohio Art.

Overall website traffic was of interest to the company because direct-to-consumer sales represented the highest-margin sales and also because Ohio Art controlled that consumer experience completely, from product copy to price. As of mid-2012, search engines referred 22% of visits to the site. Thanks to the bloggers, there were 365 sites linking to OhioArt.com and 110 sites linking to World-of-Toys.com. Of the search-generated traffic, Ohio Art accounted for 25% of visits and some version of "Etch A Sketch" almost 40%.[7]

Ohio Art had e-mail addresses for approximately 18,000 customers, which were primarily collected from orders placed on the company's website. Many of those orders were for bulk quantities, intended for events where the number of products a customer needed exceeded what a local store might keep in stock. Ohio Art had used these e-mails to send new product announcements and promotional codes to encourage orders from its website.

Management at Ohio Art was convinced that finding marketing investments that produced trackable, positive returns would be the key to its future success. It was no longer acceptable to take the risks associated with expensive national television ad campaigns and the associated inventory and receivables risk required to support broad retail distribution. The new philosophy was that as returns could be demonstrated, marketing investments could be rapidly scaled behind successful campaigns.

So when Mitt Romney's campaign manager said the candidate's platform was "…almost like an Etch a Sketch," the Ohio Art team had a decision to make: either have its staff and ad agency jump into social media to capitalize on the opportunity or stay the course with other targeted efforts.

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[6] Josh Constine, "Pinterest Hits 10 Million U.S. Monthly Uniques Faster than Any Standalone Site Ever—comScore," February 7, 2012, http://techcrunch.com/2012/02/07/pinterest-monthly-uniques/ (accessed Jul. 24, 2012).

[7] "Statistics Summary for OhioArt.com," http://www.alexa.com/siteinfo/ohioart.com (accessed Jul. 24, 2012).

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Paid Search Advertising

You're in the market for a baseball cap, an espresso maker, and a Ferrari F430 (lucky you). You decide you'd like to purchase each of the items in an online auction. You'd like to pay $10 for the hat, $1,000 for the coffee maker, and $150,000 for the Ferrari, so you set aside $151,010 to make sure you land your items.

Without understanding the nuances of the bidding structure, you decide to take an average of your total budget and allocate that as your bid amount on each item—$50,336.67 for the hat, $50,336.67 for the espresso maker, and $50,336.67 for the Ferrari.

Much to your dismay, you later learn you've won the auctions for the hat and espresso machine but missed out on the Ferrari. As ridiculous as the strategy sounds, this is what can happen when businesses run paid search advertising campaigns without trying to optimize or target their efforts to the business context and nuances of the system at hand.

Imagine that instead of different products such as hats and Ferraris, you are targeting customers with different levels of worth. Modern paid search advertising campaigns are based on the technology of online auctions—they allow businesses to bid on the opportunity to put their ads in front of certain types of customers. Fortunately, there is no need for companies to divide their budget equally and throw the same amount of money at every customer regardless of his or her expected value. Instead, the campaigns generate enough data about those customers to ensure that the companies know what the customers' values are before deciding whether it is worth it to place their ad in front of them.

Using linear and logistic regressions and cluster analyses, modern marketing managers can optimize their paid search advertising campaigns to ensure that they don't spend $50,000 on a customer who only wants to buy a hat. In this note, you will learn what paid search advertising is, the principal metrics used to track the success of the campaigns, the strategic objective of paid search, the relationship between customer lifetime value and search ads, how to overcome sparse data problems using keyword clouds, and the nature of Google AdWords's enhanced campaigns.

What Is Paid Search?

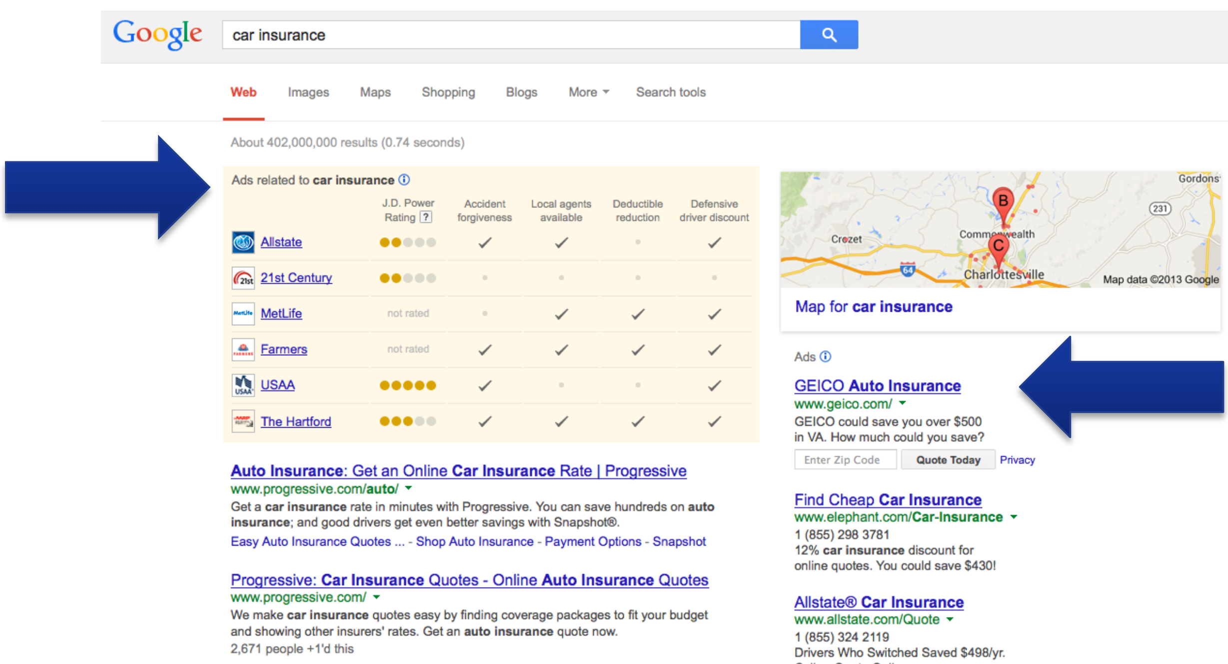
Paid search advertising is one strategy companies can use to increase their digital visibility. It is part of a broader view of search engine optimization (SEO), the method of improving a company's performance in keyword searches on popular search engines (e.g., Google, Bing, and the like).

When a user types keywords into a search engine (e.g., "car insurance"), two types of results are listed: websites the engine's algorithm has organically determined to be valuable and websites advertisers have paid to promote based on the keyword searched (see **Figure 1**). Because of the large amounts of data produced in paid search advertising campaigns, the returns from paid search advertising can be improved through marketing analytics, whereas organic search results are influenced more by website architecture.

The structure of paid search advertising has become increasingly complex as additional granularity has been introduced into the process, but the basis is still the maximum "cost-per-click" (CPC) bid, which is the highest amount an advertiser would be willing to pay for an individual click. The search engine will typically sell the link placement to the highest bidder at a rate just above the next-highest bid. This means the maximum cost per click a company would be willing to pay can be considerably higher than the average cost they actually pay. To control spending, search engines allow marketers to specify maximum daily spends. For more information on how search engines determine CPC and an ad's rank among other search results, please see the **Appendix**.

The search engine provider allows the advertiser to bid how much it would be willing to pay for the user to click on its link (a "pay-per-click" pricing structure). If the company's bid is high enough, its ad will be placed at the top of the page. Although payment is made only when someone clicks on the ad, the advertiser can be pushed farther down the page if competitors' ads are more effective at producing clicks. In **Figure 1**, Progressive is the first company listed in the organic search returns, and Allstate and Geico are listed at the top of the two groups of paid search returns.

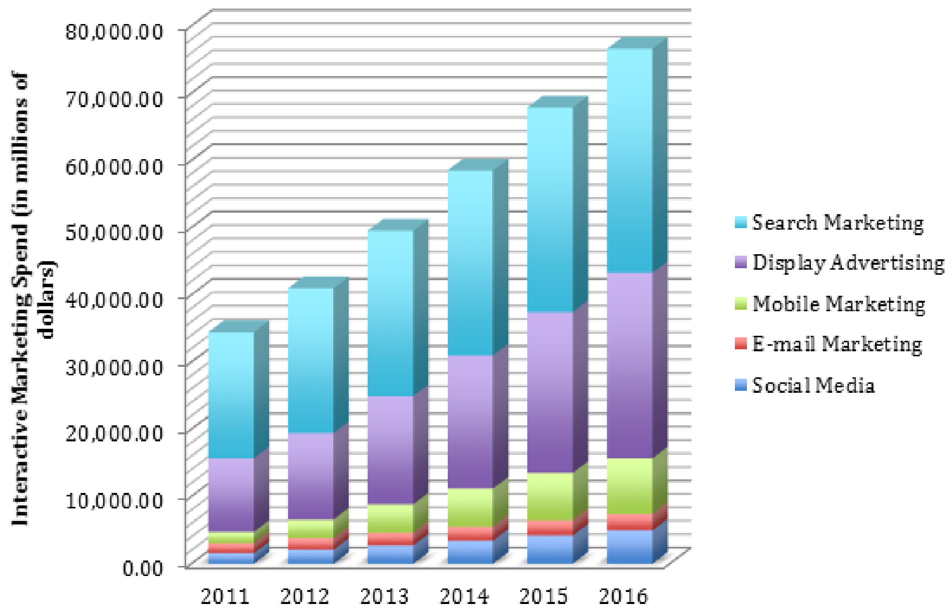
Figure 1. Paid search results.



Source: https://www.google.com/#q=car+insurance. Google and the Google logo are registered trademarks of Google Inc., used with permission.

Although search is only one of the platforms companies can use to increase their digital visibility, it is the dominant online marketing vehicle and is still growing (see **Figure 2**). Display advertising has been growing faster than search in recent years, but digital media remains largely weighted toward search. Search advertising is distinctive from most other forms of marketing media in that it targets intent: it captures prospective customers right at the moment they are expressing an interest in a company's product. This makes for a powerful tool that can deliver a robust return on investment if the company can deliver an offer that resonates with the customer.

Figure 2. Interactive marketing spending in the United States, 2011–16.



	2011	2012	2013	2014	2015	2016	CAGR
Social Media	$1,590	$2,119	$2,760	$3,453	$4,217	$4,995	26%
E-mail Marketing	$1,510	$1,694	$1,875	$2,066	$2,262	$2,468	10%
Mobile Marketing	$1,652	$2,777	$4,238	$5,697	$7,057	$8,237	38%
Display Advertising	$10,949	$12,860	$16,085	$19,783	$23,919	$27,600	20%
Search Marketing	$18,756	$21,553	$24,613	$27,515	$30,433	$33,319	12%
TOTAL	**$34,457**	**$41,003**	**$49,571**	**$58,514**	**$67,888**	**$76,619**	**17%**
Percent of All Ad Spend	19%	21%	25%	29%	32%	35%	

Data source: Forrester Research Interactive Marketing Forecasts, 2011–16.

Furthermore, modern paid search systems allow their advertisers to stipulate exactly what they are willing to pay for a given customer based on everything they know about him or her. This auction process can account for the specific search terms entered into a system ("car insurance" versus "cheap car insurance"), the type of device on which the search is being conducted, the time of day of the search, and the location of the person searching, allowing a company to bid different amounts based on how valuable they think the searcher might be. For example, data generated by companies using paid search advertising has shown that people are more likely to buy at certain times of the day than at others. Individuals searching at 1:00 a.m. might just be making a wish list, but those searching at 9:00 a.m. while at work typically are trying to be more efficient.

It is important to remember that paid search advertising is different from traditional advertising, which pushes a firm's message to consumers even when they are not looking for its products. Direct mail, store signage, and television advertisements (to name a few) are capable of creating demand by putting a company's message in front of people who have been identified as likely customers but who don't yet realize they want its products. This is a powerful form of advertising in that the advertiser has complete control of the campaign, but it isn't the way search works. Search is more akin to the yellow pages in that the advertisement for a plumbing service shows up when someone is looking for a plumber.

Again, paid search advertising can be an effective marketing channel, but it is most likely to capture only existing demand. If you have a new product or service that no one has ever heard of, search may not be as effective.

Google is the largest and most important player in the paid search advertising arena. The search engine has captured about 80% of the market for these types of ads and essentially makes the rules of the game. Bing is also a player, holding most of the remaining 20% of the market share. Comparison shopping engines such as Shopzilla and Amazon also deserve attention from companies whose products are sold in those arenas. Other pay-per-click advertising mediums such as the one offered by Facebook are focused on display ads pushed toward people who have expressed an interest in categories of products and lifestyles.

Metrics of Search Advertising

Before examining the efficacy of a paid search advertising campaign, marketers should be familiar with several metrics used to understand web traffic in general. The "visits" metric measures the number of sessions on a website, whereas the "visitors" metric measures the number of people making those visits. ("Visitors" and "unique visitors" are the same metric.) When a user creates a shopping cart on a website that does not result in a purchase, this is known as abandonment, and the abandonment rate is the ratio of the number of abandoned shopping carts to the total number of carts created by users. **Table 1** offers a list of terms useful for understanding paid search advertising metrics.

Table 1. Paid search advertising metrics.

Keyword	Term identified as one a customer might use to search for a given product.
CPC Bid	The amount an advertiser is willing to spend to place its ad in front of a potential customer given the keywords entered, device used, geographic location, and other factors.
Quality Score	An estimate of how relevant your ads, keywords, and landing page (website to which your ad points the customer) are to a person seeing your ad.
Realized CPC	The actual amount an advertiser spends to place its ad in front of a potential customer. This cost is determined as a function of bid amount, amount of the next-highest bid, and quality score.

Source: Created by case writer. Definitions are adapted from Paul W. Farris, Neil T. Bendle, Phillip E. Pfeifer, and David J. Reibstein, *Marketing Metrics, The Definitive Guide to Measuring Marketing Performance* (Upper Saddle River, NJ: FT Press, 2010).

The success of a paid search advertising campaign is dependent on its ability to put the right message in front of the right consumer and influence him or her to perform an action. Impressions represent the number of opportunities consumers are given to see an advertisement. Many recorded impressions are not actually perceived by the intended viewer, however, so some marketers refer to this metric as "opportunities to see."

Less refined metrics for understanding how often an ad is viewed are page views and hits. Page views represent the number of times a website is accessed, and hits are a measure of file requests by a website. The notion of page views was intended to more accurately measure the number of times a site has been displayed to a user. But for marketing purposes, a further distinction must be made as to how many times an advertisement has been viewed by unique visitors. For example, the advertisement may be a banner ad that changes depending on the visitor. So, for a single advertisement served to all visitors on a site, impressions are equal to the number of page views. If a page carries multiple advertisements, the total number of all ad impressions will exceed the number of page views.

Cost per impression, CPC, cost per order, and cost per customer acquired are the most critical marketing metrics for paid search advertisers. All four are calculated in the same way: by dividing advertising cost by, respectively, number of impressions, number of clicks, number of orders, and number of customers acquired.

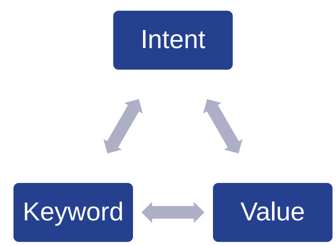
Click-through rate is the percentage of impressions that lead a user to click on an ad. It describes the fraction of impressions that motivate users to visit the web location intended by the advertiser. Most internet-based businesses use click-through metrics, and the growth of paid search advertising has made them more common. Advertisers should remember, however, that click-throughs are only a step on the road to a final sale, and other metrics must be observed to understand the true value of a paid search ad.[1]

Strategic Objective

The goal of paid search advertising is in many ways to marry the ad a company is serving—and the price it is willing to pay for it—to the intent of the consumer at the moment he or she sees the ad (see **Figure 3**).

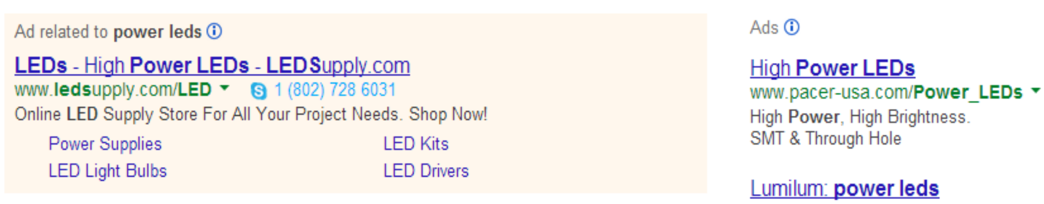
The two most common types of ads are text ads, which contain roughly a dozen words (see **Figure 4**), and product listings, which are more pictographic and are growing in importance for e-commerce (see **Figure 5**). Both types of advertisement must have messages that are appropriate and attractive to a user based on what he or she is searching for.

Figure 3. Strategic objective.



Source: All figures, unless otherwise noted, were created by author.

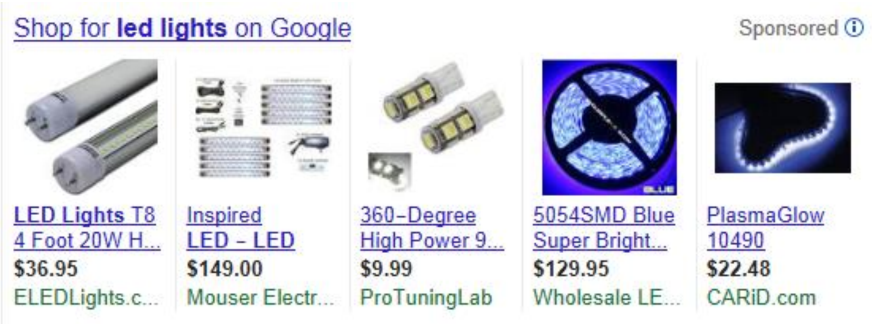
Figure 4. Google text ad.



Source: Google search, https://www.google.com/search?q=achron+power+leds&oq=achron+power+leds&aqs=chrome..69i57.3188j0j8&sourceid=chrome&espv=210&es_sm=122&ie=UTF-8#es_sm=122&espv=210&q=power+leds (accessed Nov. 14, 2013). Google and the Google logo are registered trademarks of Google Inc., used with permission.

[1] For more information on digital marketing metrics, refer to chapter 9 of Farris, Bendle, Pfeifer, and Reibstein, *Marketing Metrics*.

Figure 5. Google product ad.



Source: Google search, https://www.google.com/search?q=led+lights&source=lnms&sa=X&ei=gOmEUuCeHpCg4AO48IDwCQ&ved=0CAUQ_AUoAA&biw=1680&bih=943#q=led+lights&start=10 (accessed Nov. 14, 2013). Google and the Google logo are registered trademarks of Google Inc., used with permission.

In paid search advertising, the goal of targeting ad copy to customers becomes even more difficult to achieve than it is when using traditional display ads. For a retailer such as Wal-Mart that sells hundreds of thousands of products, that means creating appropriate ad copy for millions of possible search-term combinations. For example, the company might want to promote high-definition televisions with one group of advertisements and women's clothing with another. That means creating a campaign that hits the top search terms for televisions (e.g., high definition, hi-def, HD, flat screen, LCD, digital television) and a completely separate campaign for clothing (e.g., blouse, skirt, dress, hosiery).

Management's challenge is not only understanding how to create copy that is relevant for those different potential search queries, but also performing controlled tests to ensure the copy resonates with the types of users who are encountering it. This improves the advertisement's click-through rate, and the search engine will come to believe that the ad is relevant and serve it to customers more often.

In addition to the ad copy, the landing page to which the customer is directed must be appropriate. Although it is simple to send every potential customer to a company's home page, most consumers expect to be taken directly to the product or service they are seeking.

The most critical piece of the paid advertising system is bidding on ad space. Determining exactly how much a company is willing to pay for which customers and setting the system up to enter the appropriate bid are complex processes. This is also where marketing analytics enters into the process, since field testing plays a critical role in optimizing bids. Because the value of all customers is not equal, the bid a company is willing to make on any piece of web traffic should be commensurate with the anticipated value of the traffic to the business. A good management system should measure the value extracted from each user and use that information to anticipate the value of similar customers in the future.

CLV-Based Optimization

One way to get the most out of paid search advertising is to set customer lifetime value (CLV) as the objective function. In other words, the goal of the campaign should be to maximize CLV. In the earliest days of paid search advertising, firms typically focused on optimizing conversion rate. But all orders are not equally valuable, so measuring sales dollars rather than conversions (or number of orders) makes more sense. Consider the example of Sticks Kebob Shop in **Figure 6**. Based on its analysis of the existing customer base, Sticks has realized that customers who first visited Sticks's website based on the keywords "kids healthy fast food" are more likely to belong to the Health Conscious segment of their customer base. Customers who first visit Sticks's website through the search keywords "convenient fast food," however, are more likely to belong to the Convenience segment. Sticks also knows from its customer database that customers in the Health Conscious segment have a CLV of $1,200 and customers in the convenience segment have a CLV of $700. This would imply that Sticks is willing to bid higher for the keywords "kids healthy fast food" than for "convenient fast food," even though the click-through and conversion rates for these keywords are similar.

Figure 6. Optimizing paid search bids to maximize CLV.

	Health Conscious		**Convenience**	
Keywords	*Click-Through Rate*	*Conversion Rate*	*Click-Through Rate*	*Conversion Rate*
"Kids healthy fast food"	35%	40%	5%	15%
"Convenient fast food"	10%	5%	40%	30%
CLV		$1,200		$700

But there is still more to the picture: profit margin rates are also different depending on the product, and return rates can vary significantly. For example, people who buy paint rarely return it, but shoe buyers return their purchases regularly.

Different orders have different values to a business in the long term, so the goal of a company engaged in a paid search advertising campaign should be to use the data it has about its existing customers' behavior to optimize CLV. For companies looking to generate only sales leads through their online ads, the process is similar, as all leads are not equally valuable. Furthermore, what happens online isn't the whole story, as some consumers browse on a mobile device before making an in-store purchase. Others shop on a laptop and then contact a call center. Companies must make an effort to capture some of this data in order to gain an accurate sense of CLV.

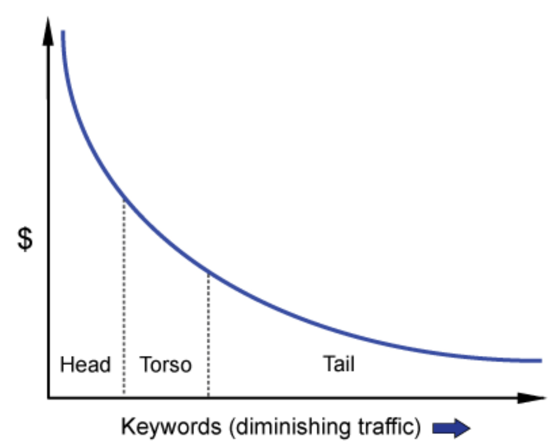
Although some of the elements of CLV might seem obvious to the marketing manager (a customer searching for "Lexus insurance" is more valuable than a customer searching for "cheap car insurance"), the ability to track the performance of a paid search ad granularly allows the manager to confirm intuition.

Keyword Clouds

A challenge does arise for companies that use a large volume of keywords, such as big-box retailers. This leads to a number of keywords with relatively sparse performance (see **Figure 7**), meaning not enough is known about the people who click on the ads after entering those words to make any significant claims about who they are relative to groups of people who click on other terms.

To account for sparse data concerns, companies must attempt to aggregate data. For example, on the keyword level, the company might group certain words with their "cousins." The firm might have sparse data

Figure 7. The long tail of keywords.



on "blue steel widgets," but it might recognize that the phrase "blue wood widgets" behaves in a similar fashion. By grouping these words into families of search terms, the business can build a statistically significant data set and make viable claims about the people who are attracted to the keywords (e.g., where they are from, how they surf the internet, or whether they are likely to be repeat customers).

On the location level, although a firm might have little data on how a keyword performs in, for instance, Charlottesville, Virginia, it might be able to create a statistically significant amount of data on small cities in the southeast with above-average income levels. That data can then be used to make assumptions about what type of keyword will be effective in those types of geographic locations.

Because there is no downside to using a very large number of keywords (the cost only increases per click, not keyword), even smaller companies may discover some of their words do not produce a large number of clicks, meaning little is known about the customers who are drawn to those words. One technique that can be useful in creating keyword clouds to optimize paid search advertising campaigns is cluster analysis. Because keywords are tied to the intent of similar consumers or consumers who are part of the same market segment, marketers can group keywords just as they would customers in a given marketplace segment. For more about how to perform cluster analyses, see "Cluster Analysis for Segmentation" (UVA-M-0748).[2]

Enhanced Campaigns

Google recognized early on that a keyword on a smartphone would be worth a different amount to a company than the same keyword on a home computer, and a keyword entered within a mile of a brick-and-mortar store would be worth more than the same keyword entered 100 miles away. So the company initially set up its system to allow users to create different campaigns for each modifier to a keyword. In other words, if a company had a base campaign of 10,000 keywords, it would create a separate 10,000-word campaign for those keywords searched on a smartphone and another 10,000-word campaign for those keywords searched on a tablet computer. If the company wanted to further modify the campaign for geography, it would have to create another three campaigns for searches within a mile of a brick-and-mortar store and another three campaigns for searches more than 100 miles from a brick-and-mortar store. This led to a replication model that was not scalable for large customers.

To correct this problem, Google rolled out enhanced campaigns in July 2013, a system that allows companies to modify their base campaigns. This meant firms had to condense back to a single version of every keyword and create a system where they could bid up for certain conditions or bid down for others. But one problem remains—the modifiers in the 2013 iteration are stacked on top of one another. For example, if a firm determined that smartphone traffic is worth 20% of desktop traffic because it is too hard to shop on the device, it might set its bid for keywords on smartphones to one-fifth of its bid on desktops. But if the smartphone search is conducted within a mile of a brick-and-mortar store, the company might believe the traffic is worth the same as desktop traffic and want to increase the bid by a factor of five. In Google's current system, this also increases the cost of desktop traffic for that keyword by a factor of five if the desktop is located within a mile of a brick-and-mortar store. If the company wanted to further customize the campaign to double its bid for smartphone users within a mile of a brick-and-mortar store who also reside in a high-value geographic location, the desktop bid would again be doubled based on the larger bid, even if that were not the intention (see **Figure 8**).

[2] Rajkumar Venkatesan, "Cluster Analysis for Segmentation," UVA-M-0748 (Charlottesville, VA: Darden Business Publishing, 2007).

Figure 8. Enhanced campaigns.

Device	Bid Amount for "Television"	Bid Amount for "Television" within One Mile of Store	Bid Amount for "Television" within One Mile of Store in High-Value Geographic Location
Laptop	5 (Base Bid)	25	50
Smartphone	1 (20% of Base)	5	10

Search engines deliver reports that marry each click to the geography from which it came, and the goal of the manager is to synthesize that information to determine the value of each type of click. For smaller businesses, Google's optimize-conversion option delivers advertisements with some success. The rules are applied across the board, however, and don't take into account CLV or conditions unique to a company, such as promotions.

Testing and Diagnostic Feedback Loops

As with any marketing measure, paid search advertising campaigns must be refined through numerous iterations. Marketing managers must gather the data available, revisit their campaigns, and make them more focused over time through testing and experiments.

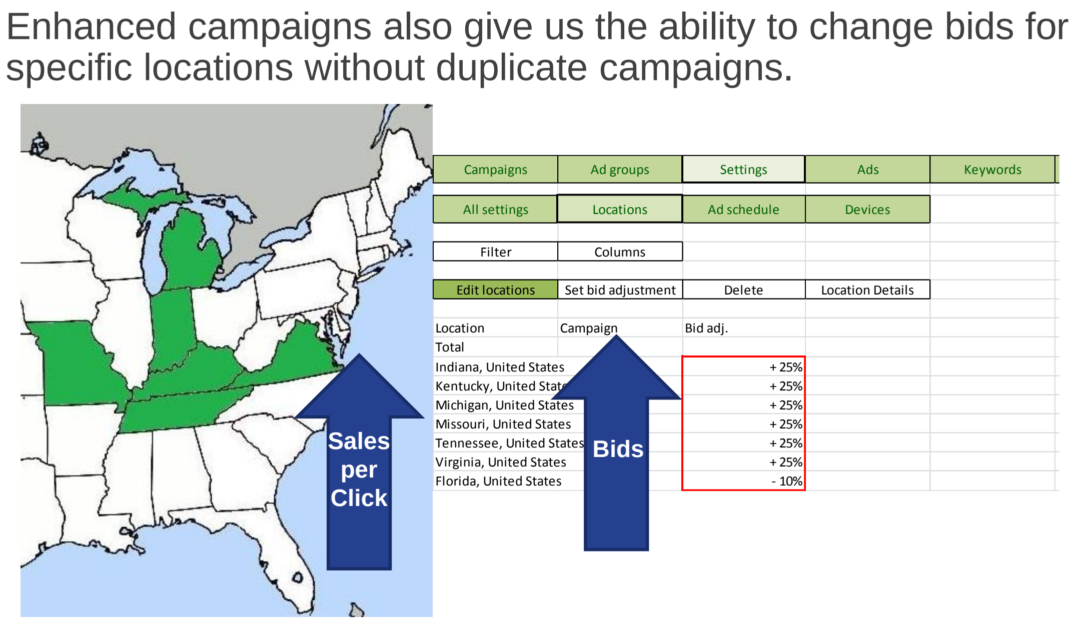
So how does the ability to target customers based on the different factors analyzed by search engines actually work in reality? Imagine Suck-It-Up Vacuums determines that the average search for "vacuum cleaner" is worth $0.45 (see **Figure 9**). The company then determines that the value is reduced 5% by the location of the search and 2.5% by the day of the week, but increased 10% because the search is on a tablet, 3% because it is done on a wireless internet connection, 7% because the search is done in the morning, and 13% because the person is a repeat buyer. All of these factors make the value of the search term at that moment $0.56.

Figure 9. Matching bids to value.

Medium	Bid
Desktop—search engine	$0.45
More than 10 miles from store	−5%
Smartphone or tablet	+20%
Free Wi-Fi hotspot	+3%
Early morning	+7%
Online retail checkout	+13%
Monday	−2.5%

As with any model, there is the danger of making assumptions based on incomplete data and omitted variables. Take a furniture retailer's campaign, shown in **Figure 10**. The company wanted to determine which regions were performing best nationally and found statistically significant differences in a variety of locations. Further inquiry, however, determined proximity to shipping locations was an omitted variable in the model. Shipping costs within 100 miles of the company's discrete distribution centers were reasonable, but outside those locations, the costs skyrocketed. Understanding that the conversion rate was higher within those regions, the company was able to correct its function to optimize CLV and target those zones more heavily than others.

Figure 10. Regional variance in value per click.



Conclusion

Paid search advertising is a powerful tool for marketers looking to match their offers with consumers who are looking for their products. Because it is an auction-like system, wherein marketers bid an amount to put their ad in front of a customer, the data available from existing customers' behavior can ensure an optimal marriage between customer value and the price of the ad.

What's more, paid search advertising systems are only growing more powerful. For now, the consumer data are somewhat limited to location, device, and search time, but the future offers far-reaching possibilities. For example, consumers might be classified according to whether they have purchased anything from a company's website in the past or whether they have put something in their cart but never made a purchase. Search engines might also be able to feed marketers data about the speed of the internet connection used by customers, whether they are at home or the office, whether they are traveling at 5 miles per hour or 60, whether they tend to buy online or offline, or whether they are existing customers of a competitor.

The basics of marketing analytics still hold true when analyzing the effectiveness of paid search advertising campaigns. The advertisements can be customized to the needs of the advertiser through varying bid amounts. Keywords represent customer intent, so they can be grouped in terms of their value just as customers can be grouped into segments. And, finally, the whole process can be improved over time through feedback loops, just like marketing measures in traditional channels.

Appendix

Paid Search Advertising

Google Paid Search Bidding Engine[1]

Let us consider three firms, Geico, Progressive, and Allstate, bidding for the keywords "cheap car insurance." As shown in **Table A1**, Geico has stated that the maximum amount it is willing to pay for a single click is \$0.40. Progressive and Allstate have stated their maximum bids as \$0.65 and \$0.25, respectively.

Table A1. Cost-per-click calculations.

Advertising Firm	Cost-Per-Click (CPC) Bid	Quality Score	Rank Number	Position	Actual CPC
Geico	\$0.40	1.8	0.40 × 1.8 = 0.72	1	\$0.37
Progressive	\$0.65	1.0	0.65 × 1 = 0.65	2	\$0.39
Allstate	\$0.25	1.5	0.25 × 1.5 = 0.38	3	\$0.01

Based on its proprietary algorithm, Google has assigned a quality score of 1.8 for Geico for the keywords "cheap car insurance." Progressive and Allstate have been assigned quality scores of 1.0 and 1.5, respectively. In general, a higher-quality score indicates that the firm's advertisement (and the firm's products) have a higher match with or relevance for the search keyword. This would imply that Google has determined that a consumer who searches for the keywords "cheap car insurance" is more likely to click on Geico's search advertisement than to click on Progressive's or Allstate's advertisements.

Google uses the product of the maximum CPC bid and the quality score to compute a company's rank number. A firm with the highest rank number is provided the top spot in the paid search advertising listing. The belief is that consumers are more likely to click on a paid search advertisement that is at the top of the list than on the ads lower down the list. In this example, Geico has the highest rank number (0.72) and is provided the top listing in the paid search advertisement section for the keywords "cheap car insurance," followed by Progressive, and then by Allstate. Although Allstate had a better-quality score than Progressive, it was given the third spot, because the maximum CPC bid provided by Allstate was much lower than Progressive's maximum CPC bid.

The final piece of information to consider is the actual CPC paid by the advertising firms. Although Geico was willing to pay \$0.40, Google charges them only \$0.37. The formula for calculating the actual CPC paid is

$$\boxed{\$0.37 = 0.65 \div 1.8 + 0.01}$$

[1] The explanation in this **Appendix** is adapted from a Google tutorial, "Search Engine Optimization Starter Guide," 2010, http://static.googleusercontent.com/media/www.google.com/en/us/webmasters/docs/search-engine-optimization-starter-guide.pdf (accessed Nov. 18, 2013).

Appendix (continued)

$0.37 is the minimum Geico would have to pay to obtain the number-one position because Progressive has a rank number of 0.65 and Geico has a quality score of 1.8. At the actual CPC of $0.37, and a quality score of 1.8, Geico's rank number is 0.67—and for a CPC of $0.36 and a quality score of 1.8, Geico's rank number would be 0.648. So, given Progressive's quality score and maximum CPC bid, Geico would need to bid only $0.37 to have the highest rank number.

Similarly, even though Progressive's maximum CPC bid is $0.65, its actual CPC is $0.39. At a CPC bid of $0.39, Progressive's rank number would be 0.39 (0.39 × 1). This would be sufficient for Progressive to have a higher rank number than Allstate.

This auction process is similar to the second-price sealed-bid system that is common in government contract jobs. In the second-price sealed-bid system, the winner of the contract is paid the price quoted by the second-lowest bidder, not the price the winning contractor itself quoted. In contrast, in a first-price sealed-bid system, the winner would be paid the amount they themselves quoted.

The variation in the paid search advertising world is the quality score. Academic research has shown that a second-price sealed-bid auction system increases the number of people willing to participate in the auction system and motivates people to bid at their true willingness to pay. The second-price sealed-bid system has been found to empirically have a higher average clearing price than a first-price sealed-bid system.

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MOTORCOWBOY: GETTING A FOOT IN THE DOOR (A)

Matt Weiss typed “sexy boots for men” into the Google search bar and sighed. He was part of a learning team at the Darden Graduate School of Business Administration participating in the Google Online Marketing Challenge, and the team’s mission was to design a Google AdWords campaign for a company that had not used the service before. The team had chosen Motorcowboy.com (Motorcowboy), a web-based manufacturer of custom boots. To develop an effective keyword list, the team needed to understand how targeted consumers searched for boots online, and to do that, it would need to adopt those consumers’ mindsets. And so it was that Weiss peered out the window of his learning team room imagining how a cross-dresser might shop online for custom boots. He knew business school would change how he thought—but not like this!

Motorcowboy

Based in Richmond, Virginia, Motorcowboy sold custom, handmade leather boots and shoes direct to customers exclusively through its website. Owned and operated by Robert Maddux, Motorcowboy was effectively a solo enterprise—Maddux oversaw operations, finances, marketing, and website management.

Maddux maintained a relationship with a family-run supplier based in Thailand. The measurements required to make the custom footwear were provided by consumers using Maddux’s proprietary self-measuring tutorial. By phone and e-mail, Maddux assisted customers with ordering and purchasing and then submitted each order directly to his supplier, who would mail the boots directly to the customer. Because Motorcowboy enabled its customers to design and request virtually any type of footwear, the business had amassed a broad portfolio of boot styles—cowboy, equestrian riding, movie replica, hiking and work, exotic material, and even superhero.

This case was prepared by Robert Maddux, owner of Motorcowboy.com and Adjunct Instructor of Management, Robins School of Business, University of Richmond; and students Timothy Harr, Martha Gray, Gautam Kanaparthi, Prateek Shrivastava, and Matthew Weiss (MBA ’11) under the supervision of Paul W. Farris, Landmark Communications Professor of Business Administration, and Phillip E. Pfeifer, Richard S. Reynolds Professor of Business Administration, Darden School of Business. The case was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

Motorcowboy's direct-to-consumer distribution strategy provided a number of benefits. With no salaried employees, Maddux spent roughly 10 to 15 hours each week responding directly to customer inquiries. Because customers paid shipping costs for the boots, and because fixed costs related to hosting and maintaining the website, 1-800 numbers, credit card expenses, and marketing were minimal, most operating margins trickled straight to his bottom line. Motorcowboy's streamlined operation enabled Maddux to capture roughly 45% to 50% gross margins on his products and still underprice competitors (**Table 1**).

Table 1. Sample sales margins and competitive pricing at Motorcowboy.

Date	Buyer Location	Product	Price	Contribution
4/19/2011	Devon, UK	Classic RAF 1936 pattern Flying Pilot boots	$649 + $79 shipping	$324.50
6/15/2011	Norway	Star Trek: Next Generation	$365 + $79 shipping	$180.00
4/13/2011	Cloverdale, Western Australia	Captain Malcolm Reynolds boots	$449 + $79 shipping	$224.50

Custom engineer/harness boots, $399
(comparable boots at competitor: $450)

Data source: Motorcowboy.

Motorcowboy.com decision process

The decision-making process that ultimately led a customer to purchase customized footwear from Motorcowboy.com involved several steps, the timing of which varied significantly. For first-time purchasers, the initial step was a web search, probably using Google, for a style and/or size of boot unavailable in mainstream shoe stores. The second step, Maddux thought, was to visit the Motorcowboy.com site, often several times, and review the product line. Days or even weeks after the initial visit, prospective customers would call or e-mail Maddux with further questions. The purpose of these communications was generally to obtain reassurance that Motorcowboy could really produce customized footwear in such a wide variety and that the measurements would ensure a good fit. Maddux believed that, before most customers would be willing to pay for a product two months in advance of delivery, they had to develop enough confidence that it would fit properly and be of sufficient quality. After the call or e-mail exchange, a typical user might take another week to three weeks to submit the measurements and place an order.

Upon placing an order, customers were asked to review the "How to measure your foot" section of the website. Only at this stage, Maddux believed, did customers take the time and effort to complete the measurement process. Fulfillment of the order would then take seven to nine weeks. Customers received e-mailed pictures of the finished product prior to shipment to ensure that the finished product corresponded to expectations.

Maddux thought that, for every 100 visitors to the site, three or five would e-mail or call to express interest; of these, one or two would place an order. Seldom were orders placed without e-mail and phone interactions with the customer (less than 5% of orders); often, multiple e-mail exchanges with attached pictures, sketches, and revised price quotes were involved.

Marketing at Motorcowboy

Before the Google Online Marketing Challenge, Motorcowboy's marketing strategy had relied on word-of-mouth advertising and strong organic search strength. Given the unique nature of Maddux's offerings, Motorcowboy often scored high for returns on "custom-made leather boots" and related searches. Maddux had acquired the business from its founder only 13 months previously and recently had begun attending police conventions to promote his products to highway patrolmen. The team saw opportunities for driving interest in selected niche segments.

To understand Motorcowboy's customer base, the Darden AdWords Challenge team met with Maddux, who identified the customer segments that supported the majority of Motorcowboy's sales and untapped segments that could benefit from Motorcowboy's value proposition.

Motorcowboy's product catered to customers who wanted boots with a custom fit but also customers who sought unique styles that catered to their unique needs and interests. Motorcycle police, required to wear boots all day long, appreciated the extreme comfort that came with custom boots. Cross-dressing men, who often had a difficult time finding stylish women's footwear to fit their larger feet, were willing to pay a premium for Motorcowboy's custom shoes. Role-play enthusiasts appreciated Motorcowboy's ability to design boots that perfectly matched those of such favorite characters as Batman or Hans Solo. In addition to these already healthy segments, Maddux wanted to grow the size of Motorcowboy's share in the equestrian and plus-size markets, as well as the market for boots made of exotic materials, such as ostrich and stingray.

The Darden team compared its notes from the meeting with Maddux to Motorcowboy's 100 most recent sales and devised a formal segmentation (**Table 2**).

Table 2. Darden team's segmentation of Motorcowboy market.

Segment (Campaign)	Status	Prospects
Motorcycle	Maddux identifies patrolmen as white space area with big upside	Large segment, strong target
Music/movie (costume)	Already accounts for significant portion of current sales	Niche market; Motorcowboy already appears high on organic search
Plus-size	New segment to target	Segment may be covered by custom-related searches
Cross-dresser	Believes segment is already purchasing product but hasn't yet targeted directly	Tiny segment but worth targeting with low spend
Equestrian	Related styles featured; segment may value custom-fit value proposition	Small segment but worth targeting with low spend
Custom	Accounts for majority of Motorcowboy's sales	Possibility of small lift
Exotic	Very small niche	Tiny segment but worth targeting with low spend

Search Engine Marketing (SEM)

Paid search was a form of Internet advertising offered by various search engines. Advertisements were tied to specific words/phrases so that, when these words were typed into the engine, the ads were displayed alongside the search results. Google, for example, sold "sponsored" listings, which appeared in a shaded box separate from natural search results. Organizations used paid search to increase their visibility in search engine results and drive traffic to their websites. Paid search was popular because it was contextual and targeted.

How SEM works

Businesses could choose to place ads on either the search engine results pages alone or both the search engine and its *network partners*—websites that partnered with the search engine to place advertisements on their webpages based on the content in the page in exchange for a share of revenue, as with a news website or a popular blog that attracted considerable traffic.

Advertisers were charged for paid search based on either the number of impressions or number of clicks on the advertisement. An *impression* was a single appearance of an advertisement on a search results page. Typically, the cost of advertisements was measured either in *cost per thousand impressions* (CPM) or *cost per click* (CPC). Most advertisers preferred to run a campaign based on a CPC basis, because clicks actually brought relevant traffic to the advertiser's website, whereas CPM was often better suited to a branding campaign with a goal of general visibility. One of the key metrics an advertiser used to determine the success of a search advertising campaign was the *click-through rate* (CTR)—the ratio of number of clicks to number of impressions.

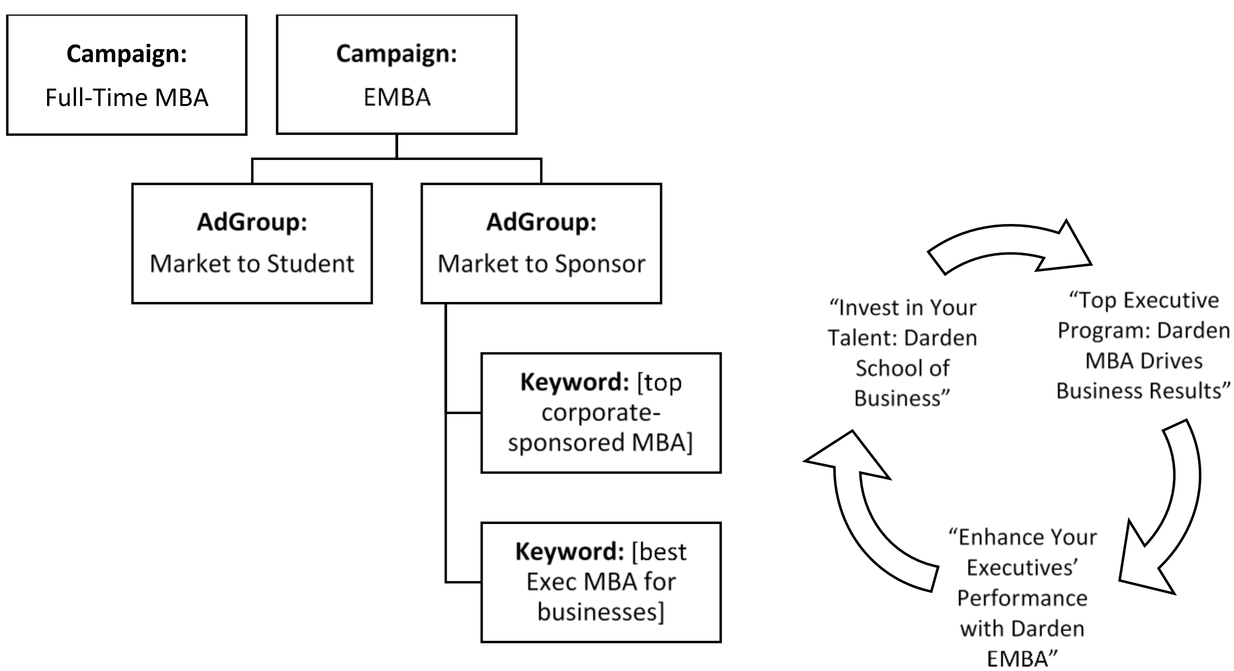
There were two ways of determining CPC for an advertisement: *flat-rate* and *bid-based*. In a *flat-rate* model, the advertiser paid a fixed amount for each click on the advertisement. In a *bid-based* model (such as that employed by Google AdWords), each advertiser indicated a maximum bid on a given keyword; every time that keyword was used in a search, an automated auction determined the order in which text ads were displayed. Similar to a Vickrey auction, a winning bidder was usually charged the same, or only a penny more, than the next highest bidder to prevent advertisers from constantly tweaking bids to minimize costs.

Dynamics of AdWords campaign

Google AdWords gave businesses leverage over advertising expenditures. A campaign targeting a particular segment or highlighting a particular product would comprise ad groups—sets of headlines and short advertisement text blurbs—which corresponded to clusters of keywords and were optimized automatically by Google based on CTR performance (**Figure 1**).

The effectiveness of an AdWords account relied on both strategic keyword selection and astute bidding. Using highly targeted keywords (e.g., "top corporate-sponsored executive MBA program in Virginia") would result in low search volume but also low demand, so a user could bid low and still acquire top page positioning and high CTR. Conversely, getting top page positioning using more general terms (e.g., EMBA) would require setting a greater *maximum bid per click* (MPC). Bidding for expensive words ensured that the advertisement would get a high number of impressions but a low CTR due to competition from other sponsored links.

Figure 1. Sample AdWords account structure.



Source: Created by case writers.

The 2011 Google Online Marketing Challenge

In 2008, Google opened the Online Marketing Challenge to college and graduate students anywhere in the world. By 2009, it had attracted more than 10,000 participants from more than 50 countries.

Structure

Teams received a budget of $200—all of which had to be spent during the campaign—to advertise online using a Google AdWords account. The teams were required to work with a local business or NGO to create effective online marketing campaigns. Participants were advised to choose clients who had not yet tried AdWords.

The competition ran from January through June, during which a campaign was required to run for three consecutive weeks. Before the campaign started, a precampaign document describing the client's business and the team's proposed AdWords strategy was to be submitted to both the supervising professors and Google. After Google's receipt of the report, $200 was credited to the account. Campaigns were actively monitored, evaluated, and tweaked to maximize impact. At the conclusion of the three-week campaign, an eight-page postcampaign summary was submitted to Google.

The 2011 competition grouped participants into three regions: the Americas, EMEA (Europe, the Middle East, and Africa), and the Asia Pacific. A winner was picked from each region and, from among those three, an overall global winner was chosen. The regional winners were invited to a major Google office in their region; members of the global winning team were awarded a week's vacation in San Francisco, including a full-day visit to the Googleplex, the corporate headquarters in Mountain View, California, in the heart of Silicon Valley.

Evaluation

Google used a proprietary algorithm to evaluate the marketing effectiveness of each AdWords account according to 30 factors. The algorithm selected the top 50 teams from each region, which were then narrowed down to five by Google AdWords experts. A group of academics assessed the pre- and postcampaign reports of those five and selected the regional and global winners.

The campaign statistics algorithm evaluated various campaigns based on the following five criteria:

1. Account structure: How well did the campaign reflect the business?
2. Optimization techniques: How well did the campaign implement best practices and suggested optimization techniques?
3. Account activity and reporting: How well did the campaign leverage data from Google's reporting center in fine-tuning its approach?

4. Performance and budget: How effectively was the budget used across keywords?
5. Relevance: What was the CTR?

Team's Strategy for the Competition

The team divided its campaign into the seven segments it had identified for Motorcowboy, each with multiple ad groups themed to specific aspects of that segment. The exotic materials campaign, for example, had an ad group for each type of material; someone searching for lizard boots would see an ad for lizard boots that would click through to a page of lizard boots on Motorcowboy's website.

Because the competition granted such a limited budget, and because Motorcowboy catered to such niche markets, the team decided to start with very specific keywords that would require lower bids than more general terms, believing that starting with a highly targeted approach would prevent exhausting funds prematurely in the search for high-value keywords. The team brainstormed lists of relevant keywords for each segment, then added qualifier terms related to Motorcowboy's unique value proposition, including "custom," "handmade," and "custom-made." (See case supplement UVA-M-0814X for the campaigns, ad groups, and keywords at launch.)

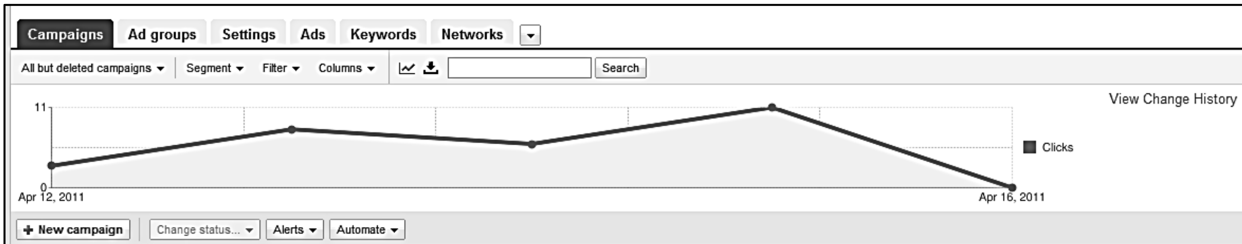
To generate the data needed to make decisions quickly, the team decided to allocate more money to the front end of the campaign. As the competition unfolded, it met regularly to determine how to tweak the campaign for maximum success. Each campaign, ad group, and keyword would be examined to determine whether it generated "quality" traffic, defined as searchers who spent time on the site and visited multiple pages. Such traffic was also described as having a low *bounce rate*, the rate at which visitors leave without moving beyond the landing page. The team also planned to monitor CTR, average ad position, and average CPC and to change bidding as necessary.

A Boot to the Backside: April 12–16

As the campaign got under way, the team closely monitored the results of its initial strategy. The team wanted to get enough data to start making decisions about which keywords were the most valuable and best targeted at the customer segment.

Four days after the launch, the team had only 28 clicks and $5.17 in ad spend (**Figure 2**). At this rate, it would spend less than a quarter of its total budget. Most of its terms were flagged by Google as "low search volume" and others as "below first page bid," meaning the bid price was too low for the ad to appear on the first page of search results.

Figure 2. Analytics of search terms.



Campaign	Budget	Status	Clicks	Impr.	CTR	Avg. CPC	Cost	Avg. Pos.
Plus Size	$2.00/day	Eligible	0	1	0.00%	$0.00	$0.00	2
Motorcycle	$14.00/day	Eligible	0	197	0.00%	$0.00	$0.00	8.3
Music/Movie	$5.75/day	Eligible	0	5	0.00%	$0.00	$0.00	3.8
Equestrian	$4.50/day	Eligible	2	217	0.92%	$0.27	$0.54	6.8
Exotic	$3.50/day	Eligible	3	277	1.08%	$0.26	$0.77	6.9
Custom	$6.00/day	Eligible	4	263	1.52%	$0.17	$0.69	3.6
Crossdresser	$5.00/day	Eligible	19	1,265	1.50%	$0.17	$3.17	4.7
Total - all but deleted campaigns			28	2,225	1.26%	$0.18	$5.17	5.3
Total - Search			28	2,225	1.26%	$0.18	$5.17	5.3
Total - Display Network			0	0	0.00%	$0.00	$0.00	0
Total - all campaigns	**$40.75/day**		28	**2,225**	**1.26%**	**$0.18**	**$5.17**	**5.3**

From a long-term strategy perspective, the team saw the value of maintaining its long list of highly customized terms, but from a practical perspective, the team knew it had to spend $200 in the allotted 21 days. What should be the team's next steps? What were the tradeoffs between this strategy and the original strategy? What metrics were most important when valuing the performance of keywords?

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MOTORCOWBOY: GETTING A FOOT IN THE DOOR (B)

Reboot: April 17–20

Looking at its slow spend rate and the poor performance of many of its keywords, the Motorcowboy team decided to take a three-pronged approach: (1) bring in more general terms that didn't use the word "custom" or other qualifiers, (2) raise the bid price for the more popular terms to no higher than $0.60, and (3) pause terms that were driving impressions but not click-throughs.

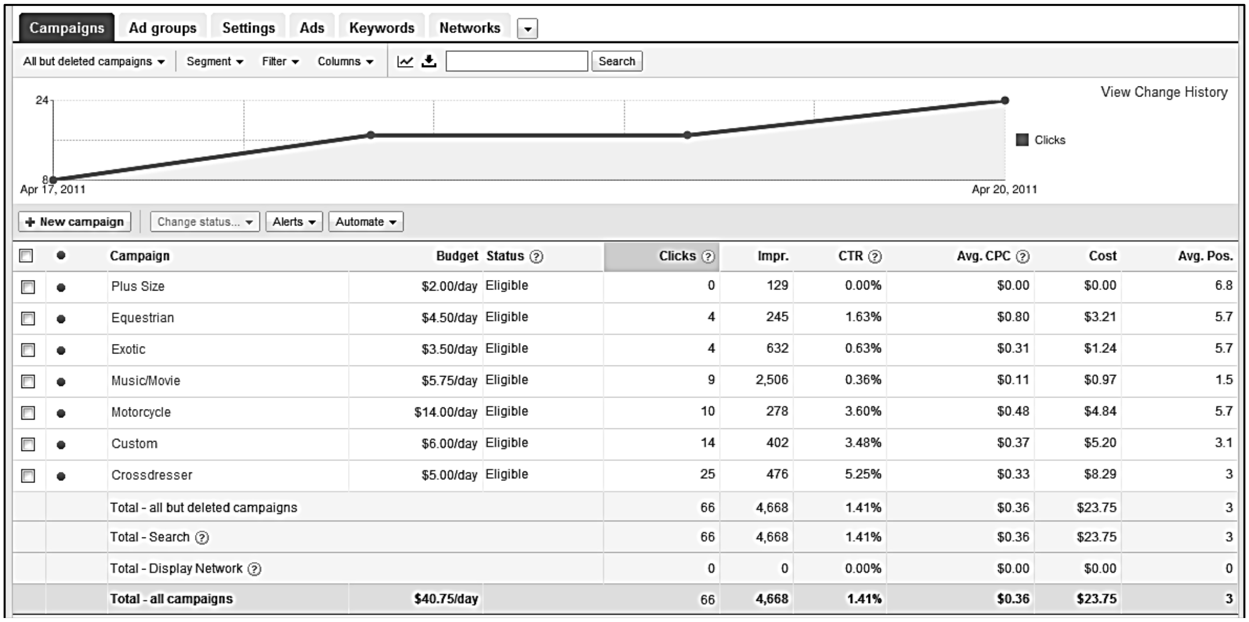
With such low click-through rates, it was difficult to determine quantitatively which terms should get the price raise. The team sought to assess words on their qualitative merits, primarily with the question, "Is the person typing in this search going to be our customer?" With raised bid prices and new keywords, the team sat back to see what would happen. Over the following four days, the newly modified account generated 66 clicks and spent $23.75 (**Figure 1**).

Despite this uptick in spending and clicks, the team was still not going to reach the required spending level of $200. But the team did believe that the cumulative total of 94 clicks could provide data in Google Analytics on the quality of traffic (bounce rate, time on site, average pages visited) generated by different keywords.

The team thought this new set of data would enable them to make necessary modifications to its campaigns. What should the team's next steps be? Should it continue down the path of increased price or look for words that could drive higher click-through volume? What other aspects of the campaign should be fine-tuned?

This case was prepared by Robert Maddux, owner of Motorcowboy.com and Adjunct Instructor of Management, Robins School of Business, University of Richmond; and students Timothy Harr, Martha Gray, Gautam Kanaparthi, Prateek Shrivastava, and Matthew Weiss (MBA '11) under the supervision of Paul W. Farris, Landmark Communications Professor of Business Administration, and Phillip E. Pfeifer, Richard S. Reynolds Professor of Business Administration, Darden School of Business. It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

Figure 1. Search data for April 17–20.



Campaign	Budget	Status	Clicks	Impr.	CTR	Avg. CPC	Cost	Avg. Pos.
Plus Size	$2.00/day	Eligible	0	129	0.00%	$0.00	$0.00	6.8
Equestrian	$4.50/day	Eligible	4	245	1.63%	$0.80	$3.21	5.7
Exotic	$3.50/day	Eligible	4	632	0.63%	$0.31	$1.24	5.7
Music/Movie	$5.75/day	Eligible	9	2,506	0.36%	$0.11	$0.97	1.5
Motorcycle	$14.00/day	Eligible	10	278	3.60%	$0.48	$4.84	5.7
Custom	$6.00/day	Eligible	14	402	3.48%	$0.37	$5.20	3.1
Crossdresser	$5.00/day	Eligible	25	476	5.25%	$0.33	$8.29	3
Total - all but deleted campaigns			66	4,668	1.41%	$0.36	$23.75	3
Total - Search			66	4,668	1.41%	$0.36	$23.75	3
Total - Display Network			0	0	0.00%	$0.00	$0.00	0
Total - all campaigns	**$40.75/day**		66	**4,668**	**1.41%**	**$0.36**	**$23.75**	**3**

Data source: Google Analytics.

UVA-M-0816
Rev. Jun. 20, 2014

MOTORCOWBOY: GETTING A FOOT IN THE DOOR (C)

Foot on the Pedal: April 21–April 28

Checking back periodically over the remainder of the competition, the Darden team continued with its approach of eliminating poor-performing terms (low click-through rate [CTR], poor analytics data) and adding the occasional new keyword. The team decided to increase bids to try for first or second ad position on ads that aligned well with Motorcowboy's core offering that had shown good CTRs thus far. With time running out, the team was also willing to place bids in excess of $1.00 on expensive keywords that were appearing to generate strong results. While it was hard to measure the value of each click-through given the long-lead nature of sales, the team believed that given the high profit margin on each purchase, driving the right type of traffic would create the value to justify a higher bid price.

With three days to spare, the team successfully exhausted its account and achieved a CTR of almost 5% during the final eight days (**Figure 1**).

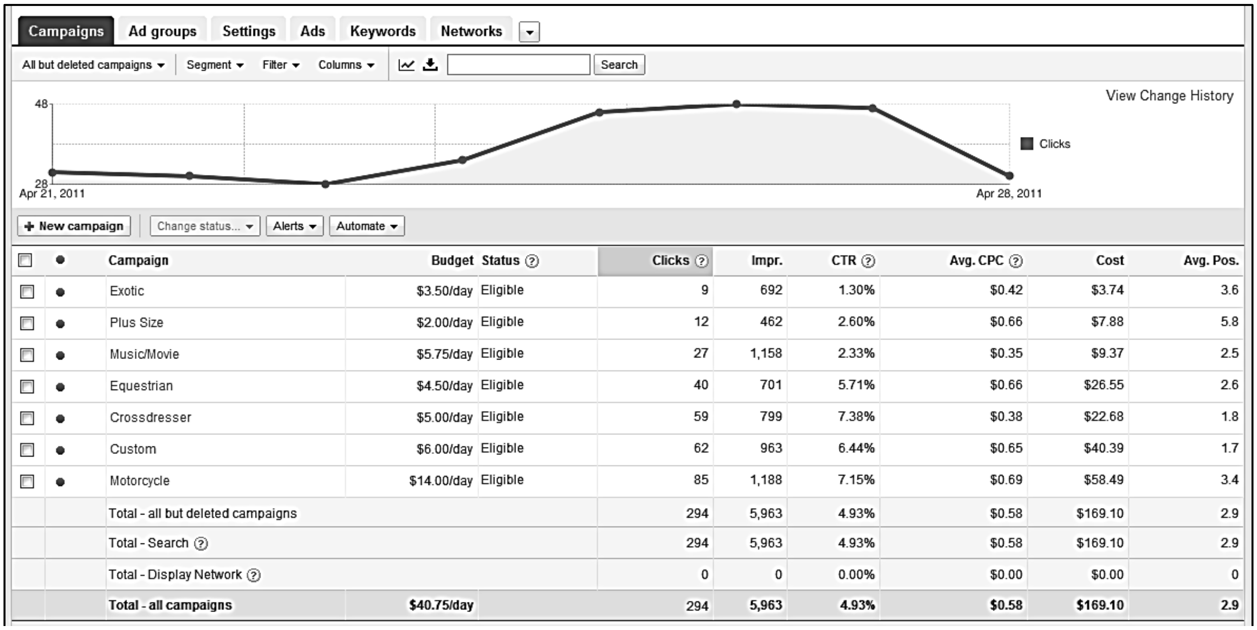
Feedback

After the competition, the Darden School team wrote the postcampaign report and debriefed with Robert Maddux, who reported a significant lift in inquiries during the competition period. Because Motorcowboy seldom processed orders through its site, however, Google Analytics would not be able to link those who connected to the site from the AdWords campaign with particular inquiries or purchases.

After parsing the data from the competition, the team contemplated a series of conclusions and recommendations (**Table 1**). They wondered if customer lifetime value (CLV) would be a good concept for Motorcowboy and whether Maddux could use paid search advertising to increase CLV.

This case was prepared by Robert Maddux, owner of Motorcowboy.com and Adjunct Instructor of Management, Robins School of Business, University of Richmond; and students Timothy Harr, Martha Gray, Gautam Kanaparthi, Prateek Shrivastava, and Matthew Weiss (MBA '11) under the supervision of Paul W. Farris, Landmark Communications Professor of Business Administration, and Phillip E. Pfeifer, Richard S. Reynolds Professor of Business Administration, Darden School of Business. It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

Figure 1. Search data for April 21–28.



Campaign	Budget	Status	Clicks	Impr.	CTR	Avg. CPC	Cost	Avg. Pos.
Exotic	$3.50/day	Eligible	9	692	1.30%	$0.42	$3.74	3.6
Plus Size	$2.00/day	Eligible	12	462	2.60%	$0.66	$7.88	5.8
Music/Movie	$5.75/day	Eligible	27	1,158	2.33%	$0.35	$9.37	2.5
Equestrian	$4.50/day	Eligible	40	701	5.71%	$0.66	$26.55	2.6
Crossdresser	$5.00/day	Eligible	59	799	7.38%	$0.38	$22.68	1.8
Custom	$6.00/day	Eligible	62	963	6.44%	$0.65	$40.39	1.7
Motorcycle	$14.00/day	Eligible	85	1,188	7.15%	$0.69	$58.49	3.4
Total - all but deleted campaigns			294	5,963	4.93%	$0.58	$169.10	2.9
Total - Search			294	5,963	4.93%	$0.58	$169.10	2.9
Total - Display Network			0	0	0.00%	$0.00	$0.00	0
Total - all campaigns	**$40.75/day**		**294**	**5,963**	**4.93%**	**$0.58**	**$169.10**	**2.9**

Data source: Google Analytics.

Table 1. Darden team recommendations for Motorcowboy (by campaign).

Custom	High CTR and increased time spent on site. A promising segment to continue targeting with AdWords.
Equestrian	The Western ad group generated substantially more and higher-quality traffic than the general equestrian ad group. Future AdWords to emphasize Western (cowboy) boots.
Cross-dresser	A highly searched campaign with low CPC. Some keywords had a high bounce rate, but several searchers spent a good deal of time on the website. Recommend continuing to invest in this segment.
Exotic	High bounce rate and low time on site; searchers did not seem to find what they were looking for. With low CPC, could potentially generate sales at low cost in the future.
Motorcycle	Keywords were slightly more expensive, but it generated a high level of good traffic, particularly in the women's segment.
Music/movie (costume)	Some ad groups generated more and better traffic than others. Recommend focusing on those that did well, such as "Wonder Woman" and "Matrix," and testing additional characters.
Plus-size	Did not generate significant or quality traffic, perhaps due to demographics or the use of more generic search terms covered under the custom campaign. Recommend focusing on custom campaign to generate plus-size customers.

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VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

Looking out the window of his office on a clear night in November 2012, Kevin Sidders contemplated his next steps. His company, VinConnect—an intermediary between European wineries and American consumers—had recently closed an offer for one of its partner wineries, and its numbers were slowly improving. But Sidders, the company's president, knew he needed to focus VinConnect's efforts on new marketing initiatives to more effectively reach its targeted audience and increase its customer conversion rate.

VinConnect's goal was to allow European wineries to sell their products "directly" (through VinConnect) to American consumers via offers delivered in e-mail. Since its launch, the company had signed up 19 partner wineries, and more than 900 people had subscribed to at least one of its winery mailing lists. It was a great start for a company that had been in business for just over a year, but Sidders knew he still had a tough road ahead.

When Sidders founded VinConnect in the fall of the previous year, the idea of European wineries selling directly to American consumers was completely novel. The initial challenge was introducing the concept to European wineries and convincing them of the benefits of the direct-to-consumer (DTC) model. Next, he had to build relationships with importers and distributors to ensure the model would work. Last, he needed to establish a reputation in the industry and put the VinConnect name and idea in front of wine buyers.

Given that there was tremendous market activity, marketing buzz, and technological innovation in the U.S. direct wine sales market, Sidders was concerned about differentiating his story and communicating his message to his target audience, and so decided to explore paid keyword search advertising. Would the powerful new tool be what he needed to get to the next level or would the data show that more traditional types of marketing were just as valuable?

By comparing the results of his Google AdWords campaigns and other outreach efforts and surveying his customers, Sidders found that the most effective ways to find qualified buyers were traditional marketing channels such as PR campaigns, strategic partnerships, and e-mail

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This case was prepared by Rajkumar Venkatesan, Bank of America Research Professor of Business Administration. It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

blasts. Sidders wondered if paid search advertising was even relevant for him and if it only attracted customers who would prove to harder to retain.

Industry Description

The wine market in the United States had been growing consistently and was expected to have a market value of $33.5 billion by 2013.[1] As of 2012, Americans could buy one of more than 15,000 SKUs[2] from more than 5,000 brands. **Table 1** illustrates the industry's growth, especially in DTC shipments:

Table 1. Wine industry metrics.

	2013	**2014**
DTC shipments	$1,468 million	$1,584 million
Total market	$8,370 million	$8,966 million

Data source: "Wine Industry Metrics," January 2014, Wines & Vines website, http://www.winesandvines.com/template.cfm?section=widc&widcDomain=home&widcYYYYMM=201401 (accessed Feb. 18, 2014).

Alcohol sales and distribution in the United States was governed by laws that dated back to the repeal of Prohibition in 1933. The result was a mandatory three-tier system wherein the production, distribution, and sale of alcoholic products had to be done by a separate entity. Each state also had its own laws regarding all facets of the distribution, sale, and taxation of alcoholic products, which made the transportation of alcohol across state lines a complex process.

Despite all this, to drive growth, U.S. wineries developed new and more advanced marketing techniques. Many wineries were increasing spending on traditional advertisements, such as in-store campaigns and advertisements in print media, whereas others focused on using DTC marketing and social media efforts to build their brands.

Direct-to-Consumer Sales

One area of particular focus for U.S. wineries was attracting private clients via direct sales models, including tasting rooms, online stores, mailing list offers, and/or wine clubs. DTC wine sales represented 3% of the overall market or more than 7 million cases sold, in the 12 months ending in April 2011.[3] Since then, there had been an increase in volume of over 8% to

[1] Research and Markets, "US Wine Market Forecast to 2012," March 13, 2012, http://www.researchandmarkets.com/reports/648785/us_wine_market_forecast_to_2012.pdf (accessed Jan. 15, 2014).

[2] Whole World Wines, "U.S. Wine Industry Info," http://www.wholeworldwines.com/challenge/us-wine-industry-info (accessed Jan. 15, 2014).

[3] *Direct-to-Consumer Shipping Report*, annual report from ShipCompliant and Wines & Vines, June 2011.

11.5%[4] of the market. In October 2012, DTC shipments hit a new record with a total value of $222 million.[5] According to Wines & Vines, DTC sales through mailing lists, clubs, and tasting rooms were growing at twice the rate of the overall market and rapidly capturing share.

Although tasting rooms had been employed to do DTC marketing for decades, beginning in the 21st century, U.S. wineries began to innovate, using mailing list offers, wine clubs, and online stores. Over this period, wineries began developing methods by which they could (with enormous regulatory compliance overhead) sell and deliver their products direct to consumers across state lines. Once a winery put the requisite infrastructure in place, customers in remote (e.g., out-of-state) areas were able to purchase wine direct from the winery and have it delivered to them. DTC wine sales provided benefits to both consumers and wineries (see **Table 2**):

Table 2. Benefits of DTC wine sales.

Consumer	Winery
Convenience	Direct communication with private clients
Supporting the winery directly	Marketing messages delivered at point of sale
Access to hard-to-find wines	Encourages clients as brand ambassadors
Provenance	Price protection and control
	Opportunity to make special offers and sell older vintages
	Increase in three-tier demand as private clients buy more through traditional channels due to their affinity and relationship

Source: Created by case writer.

VinConnect's model aimed to capitalize on the growth of the wine industry, specifically the increase within the DTC segment. The company enabled European wineries to market directly to private clients via mailing list offers, just like U.S. wineries were able to. In addition to helping create the mailing lists through customer acquisition, VinConnect developed marketing programs for private clients that provided a communications and commerce strategy, a legal and compliance infrastructure, logistics capabilities, and customer service.

European wineries faced a particular disadvantage in the U.S. wine market. Due to the legal and logistical challenges of the U.S. regulatory framework, European wineries had been unable to market to private clients in the United States, and therefore faced a competitive disadvantage and had a limited share of the U.S. luxury wine market. By finally allowing top European wineries to find and directly market to top U.S. customers, VinConnect enabled the wineries to take advantage of the benefits of DTC wine sales and to compete more effectively in the United States.

[4] *Direct-to-Consumer Shipping Report*.

[5] "Wine Industry Metrics," October 2012 data, Wines & Vines website, November 15, 2014, http://www.winesandvines.com/template.cfm?section=widc&widcDomain=home&widcYYYYMM=201210 (accessed Feb. 18, 2014).

VinConnect, Inc.

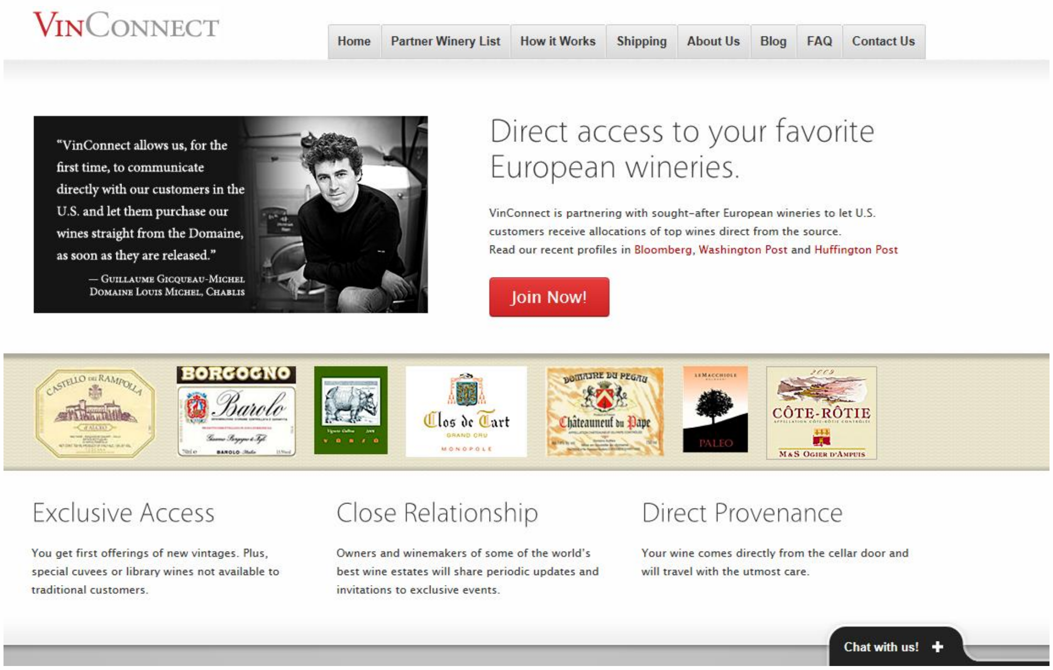
Prior to moving to Charlottesville, Virginia, Sidders lived in San Francisco, California, where he enjoyed discovering new wineries in the Napa Valley area. As he found emerging wines that were of high quality but limited production, he joined their mailing lists to have a direct relationship with them, support them financially, and ensure he would receive an annual allocation of highly sought-after wines.

Sidders' love of wine extended to French and Italian bottling, but he found the process of purchasing similarly high-quality, limited-production imported wines to be challenging. What might be available in one shop often wouldn't be in another, and the few bottles that might come to a local store often would sell out quickly. He turned to the Internet to continue to search for the wines, but that presented its own issues: he faced widely varying pricing and availability, he could never be assured of the provenance of the wine or how it had been stored or transported, and he had no direct relationship with the seller to ensure the wine's safe arrival (or recourse in the event it did not).

In response, Sidders founded VinConnect, Inc., in September 2011, to provide a way for the world's best wineries to sell their wines direct to private clients in the United States. VinConnect acted as the DTC channel in the United States for its luxury European winery partners by creating and administering mailing lists and club programs that enabled U.S. customers to buy wine directly. Each partner winery had its own mailing list and offered wines it selected at the frequency it chose (**Exhibit 1**). The wines were then transferred to the United States, forwarded along to VinConnect's warehouse in Sonoma, California, and shipped to customers.

When a consumer was interested in joining a winery mailing list, he or she could visit VinConnect.com (**Figure 2**) and click on one of the many "Join Now" options. From there, the potential customer entered his or her mailing address and selected which of the available winery mailing lists to join. Subscribers then began receiving periodic news and offers from those wineries. Each winery differed: some made offers once a year and others allocated wine a few times throughout the year. For more information about VinConnect's subscribers, see **Exhibit 2**.

Figure 2. VinConnect website.



Source: VinConnect. Used with permission.

When a subscriber received an offer, he or she was asked to reply within a specific period of time, usually two weeks. At the close of the offer window, all orders were processed and customers received an order confirmation that included a general time frame for expected delivery. Delivery could take anywhere from two weeks to three months, depending on the type of allocation and where the wine was being sent. In 2012, VinConnect shipped to 38 states in the United States.

The customer response could come via e-mail or phone call, and if it was a first order, VinConnect would reach out to the customer directly in order to configure an account, including shipping and billing information. Once the order was confirmed, the customer did not hear from VinConnect again until the wine was received in inventory. At that point, the customer was charged and a receipt was sent. Tracking information was sent once the wine had been shipped.

Recent Marketing Initiatives

When VinConnect first launched, it grew its list of subscribers through word-of-mouth advertising and by taking advantage of basic digital marketing, including Twitter, Facebook, and organic Google searches. Having developed a profile of what he believed his target market to be, Sidders assumed that customers in the United States seeking wines produced by VinConnect's partner wineries would naturally be excited about this new avenue for purchasing direct. At an average of $80 per bottle, Sidders expected his company's gross profit margins to be around 30% to 40%. Unfortunately, the number of purchases had not been as high as he projected. Although people seemed to be excited about the VinConnect concept and the open rates for e-mails were high**,** those who received the wine offers often did not buy the wine. In an effort to attract the appropriate subscribers, Sidders invested in a number of different initiatives, including creating Google AdWords campaigns and strategic partnerships. The question was, which of the measures would be most effective at finding customers who would be more likely to buy wine than the existing base?

Paid Search Advertising

Sidders created a variety of Google AdWords campaigns, each focusing on one of his partner wineries. Rather than using words about buying wine direct from wineries, he chose keywords that supported the idea that VinConnect was developed to create the connection between top European wineries and the American consumers who already appreciated its wines: Sidders used the proper names of the wineries that partnered with VinConnect. **Exhibit 3** shows performance data for each of the keywords that attracted at least one visit to the VinConnect website. On average, VinConnect was spending $300 to $400 on Google paid search advertising per month. But the campaigns had not shown the return on investment that Sidders had hoped for, instead yielding only a small number of customer conversions (during the 14 months when paid search advertising was active) relative to other marketing channels (**Table 3**):

Table 3. Keyword conversions.

Keyword	Sign-ups
Borgogno	11
Castello dei Rampolla	1
Ciacci Piccolomini	11
La Spinetta	9

Source: Company documents.

Sidders also launched a small pay-per-click Facebook campaign that showed few returns. The assumption was that the program did not attract the right consumers because Facebook's system allowed users to opt into certain categories rather than search for specific keywords.

Public Relations and Strategic Partnerships

As soon as VinConnect was launched, participants in online forums on wine-centric websites, such as wineberserkers.com, began discussing the company. Then, in February 2012, the Terroirist wine blog contained an article profiling the company and Sidders, giving VinConnect exposure to the niche market it was created to benefit. Seeing the increase in subscribers due to this exposure, Sidders hired a public relations specialist to increase awareness of VinConnect and gain additional subscribers.

Throughout summer 2012, Sidders participated in a number of interviews, and VinConnect was featured in two notable articles. The first article, published June 14, 2012, was written by columnist Richard Jennings in his blog for the *Huffington Post*. In his commentary, Jennings wrote, "I'm very excited at this new option for U.S. wine lovers to buy direct from some of Europe's greatest. I also think Kevin and his team have done an admirable job in setting up a model that's as transparent and simply aimed at connecting producers with their U.S. fans as possible."[6] On August 28, 2012, Elin McCoy from *Bloomberg* wrote an article about VinConnect entitled "Former Credit Suisse Banker Sells Exclusive Wines."

To attract the attention of groups of individuals who would likely be ideal VinConnect customers, Sidders also began to pursue strategic partnerships with organizations that might have a particular interest in purchasing luxury wines. The first such partnership was with a national organization of business executives called the Business Leaders Association (BLA);[7] the organization had a wine-related special interest group that was focused on sharing and appreciating the world's top wines.

Surveying the Customer Base

To measure the effectiveness of his marketing methods, Sidders contracted with an outside firm to design a 17-question survey and distribute it to three groups of VinConnect subscribers: customers, known as prospects, who opened VinConnect e-mails but did not buy wine (Group A); one-time purchasers (Group B); and frequent purchasers (Group C). Group A was 83% male, the majority (58%) of whom were between the ages of 31 and 50. Group B was 89% male and skewed slightly older: 51% were between the ages of 31 and 50, and 21% were between the ages of 51 and 60. Group C was 96% male and the oldest group of the three: 80% of the survey respondents were between 41 and 60 years of age. See **Exhibit 4** for all relevant survey results.

Group C, the frequent purchasers, most often (41%) had heard about VinConnect through a news publication, such as the articles in the *Huffington Post* and *Bloomberg*. Group A survey respondents were most likely to have found VinConnect through a wine-related website (36%) or an online search (21%). Only 4% of the customers who purchased wine regularly had found VinConnect through a search engine such as Google.

In terms of the outlets from which the survey respondents most likely purchased wine, the frequent purchasers were less likely to buy from grocery stores or large retailers than the group that had never purchased a bottle from VinConnect. But both groups showed a willingness to purchase wine on the Internet. Purchasers in Groups A and B showed similar reasoning for making a decision to purchase a particular wine, but Group C reported two notable differences.

[6] Richard Jennings, "New Direct-to-Consumer Channel for Top European Wines: VinConnect," *Huffington Post*, June 14, 2012, http://www.huffingtonpost.com/richard-jennings/new-directtoconsumer-chan_b_1592124.html (accessed Jan. 15, 2014).

[7] The organization has been disguised.

Reviews and online scores rated most highly with the frequent-purchaser group, and quality/price ratio was less important for those buyers than for the other two groups.

Group C also showed marked differences in the aspects of the VinConnect model that attracted them to join. The frequent-purchaser group was more influenced by three factors in particular: (1) direct support (their purchases supported the winery directly), (2) priority offers (they had the first opportunity to purchase new releases before they were available in the United States), and (3) assured provenance (they had knowledge that the wine was authentic and traveled through winery-approved, temperature-controlled channels).

The survey was instrumental in proving to Sidders that the strategic partnership with BLA was successful at drawing new customers who were more likely to buy VinConnect wines than previous subscribers had been. **Table 4** shows the performance of each of VinConnect's partner wineries, broken down by type of customer (Group B or C) and which marketing channels drew the customers to the company:

Table 4. Winery performance data.

Winery	Sign-Ups	Group C	Group B	Revenue	Keyword	BLA	Facebook	*Bloomberg/ Huffington Post*
Artadi	0							
Borgogno	401				29	31	7	7
Castello dei Rampolla	401	20	14	12,600	39	26	11	7
Castello del Terriccio	271	8	4	3,912	39	16	9	6
Chateau Musar	0							
Ciacci Piccolomini	283	10	1	2,031	31	16	8	9
Clos de la Chapelle	0							
Clos de Tart	595	8	9	26,641				
Dr. Loosen	0							
E. Pira—Chiara Boschis	232	13	5	4,389	25	12	9	4
Etienne Sauzet	0							
Fontodi	274				35	11	10	4
Gourt de Mautens	310	8	10	6,077	25	17	6	4
Il Carnasciale	1							
La Massa—Giorgio Primo	383	8	2	3,930	35	34	9	7
La Spinetta	411				47	22	11	13
Le Macchiole	438				34	34	12	8
Louis Michel	416	23	14	8,401	42	27	12	3
M & S Ogier	359				28	23	7	3
Massolino	497	25	2	6,105	40	31	9	11
Monteverro	0							
Pegau	420	18	8		41	21	11	4
Pelissero	319	17	1	1,945	29	20	9	8
Robert Weil	0							
Roberto Voerzio	366	2	6	16,800	34	24	11	7
Vall Llach	0							
Vielle Julienne	444		2	133	39	31	10	4
Vincent Girardin	277	23	6	7,664	41	8	4	4

Source: Company documents.

Decisions

After the dust had settled on VinConnect's new marketing measures, the company had 20 partner wineries and more than 1,000 subscribers. Still, only a small percentage of those who had signed up and were receiving offers were actually purchasing wine. Sidders reviewed the analytics from his website from September 19, 2011, through November 19, 2012 (**Exhibit 5**). He knew he needed to determine what to do next to increase VinConnect's conversion rate and also to decide about how to allocate resources among marketing strategies to ensure the most profitability moving forward. He wondered which of the events of the previous months had had the largest effect on obtaining additional subscribers and which had helped VinConnect obtain actual customers. He asked himself: Was he even attracting the correct audience? Did he need to offer additional services?

Exhibit 1

VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

List of Wineries

Winery	Top Wine(s) Varietals	Recent Top Scores	Price	Points of Distinction	Production
BURGUNDY/CHABLIS					
Clos de Tart	Pinot Noir	Mid 90s	$$$$$	Legendary Grand Cru, low yields, built to age	Tiny
Louis Michel	Chardonnay	Low 90s	$$ –$$$	Lean, mineral, pure — no oak used in vinification	Small
Vincent Girardin	Pinot Noir, Chardonnay	Mid 90s	$$ –$$$$	Pure, elegant, balanced	Medium
RHONE VALLEY					
Gourt de Mautens	Grenache blend	Mid 90s	$$$	Hand-crafted, rich and intense	Tiny
Pegau	Grenache blend	Mid 90s to 100	$$$ - $$$$	Traditonal — ripe, gamy, rustic, spicy	Small
M & S Ogier	Syrah	High 90s to 100	$$ - $$$$$	Pure artisinal Syrah — deep, full, precise	Small
Vieille Julienne	Grenache blend	Mid 90s to 100	$$ - $$$$$	Biodynamic, classic, elegant, very old vines	Tiny
PIEDMONT (BAROLO AND BARBARESCO)					
Borgogno	Nebbiolo (Barolo)	Low to Mid 90s	$$ - $$$$	Traditional, classic, long aging	Small
E. Pira – Chiara Boschis	Nebbiolo (Barolo)	Low to High 90s	$$ - $$$	Feminine approach - structured, elegant, perfumed	Tiny
La Spinetta	Nebbiolo (both)	Mid 90s	$$ - $$$$	Rich, deep fruit, high quality across broad range	Large
Massolino	Nebbiolo (Barolo)	Low to Mid 90s	$$ - $$$	Structured, age-worthy, powerful	Small
Pelissero	Nebbiolo (Barbaresco)	Low to Mid 90s	$$ - $$$	Dynamic, consistent, refined	Small to Medium
Roberto Voerzio	Nebbiolo (Barolo)	Mid to High 90s	$$$$ - $$$$$	Iconic wines, very low yields, dense fruit	Tiny to Small
TUSCANY (CHAINTI, BRUNELLO AND SUPER TUSCAN)					
Castello dei Rampolla	Cab Sauv, Sangiovese, others	Mid 90s to 100	$$ - $$$$	Biodynamic, pure, fruit-driven	Small
Castello del Terriccio	Cab Sauv, Sangiovese, others	Mid 90s	$$ - $$$$	Powerful, expressive, age-worthy	Small to Medium
Ciacci Piccolomini	Sangiovese (Brunello)	Low to Mid 90s	$$ - $$$	Classic, age-worthy	Small to Medium
Fontodi	Sangiovese (Chianti)	Mid 90s	$$ - $$$$	Powerful, rich, reference Chianti	Medium
Il Carnasciale	Caberlot	Mid to High 90s	$$$ - $$$$	Unique varietal, deep, complex, balanced	Tiny
La Massa – Giorgio Primo	Cab Sauv, Merlot	Low to High 90s	$$ - $$$	Rich fruit, great balance	Small
Le Macchiole	Cab Franc, Merlot, Syrah	Mid to High 90s	$$$ - $$$$$	Single varietals, powerful yet balanced	Small

Source: "Winery Partners," VinConnect website, http://vinconnect.com/wineries/ (accessed Jan. 31, 2014).

Exhibit 2

VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

Subscriber Information

Customer	Referred By	Select Winery Mailing Lists	Date/Time of Sign-up	Date of Most Recent Change
Customer 1			6/17/2011 13:02	7/5/2011 9:05
Customer 2			6/15/2011 16:51	7/5/2011 9:05
Customer 241	Facebook Ad	Clos de Tart (new sign-ups will be Wait List), Louis Michel, Vieille Julienne, Borgogno, Massolino, La Massa, Le Macchiole	1/5/2012 21:19	5/31/2012 8:22
Customer 266	wineberserkers	Clos de Tart (new sign-ups will be Wait List), Louis Michel, M&S Ogier, La Spinetta, Pelissero	1/24/2012 17:44	2/14/2012 9:51
Customer 330	La Spinetta	E. Pira - Chiara Boschis, La Spinetta, Massolino	2/18/2012 7:22	7/17/2012 11:50
Customer 390	google ad	Louis Michel, Borgogno, La Spinetta, Massolino, Roberto Voerzio, Le Macchiole	3/14/2012 13:04	3/14/2012 13:04
Customer 392	saw you on facebook	M&S Ogier, Borgogno, La Spinetta, Massolino, Roberto Voerzio, Castello dei Rampolla, La Massa, Le Macchiole	3/14/2012 17:16	3/14/2012 17:16
Customer 399	YPO	Clos de Tart (new sign-ups will be Wait List), Louis Michel	3/16/2012 9:26	3/16/2012 9:26
Customer 522	Terroirist.com	Vieille Julienne, VinConnect Special Offers	6/15/2012 23:55	10/16/2012 23:17
Customer 592	Richard Jennings Blog	Clos de Tart (new sign-ups will be Wait List), Pegau	7/12/2012 16:24	7/12/2012 16:24
Customer 593		La Spinetta	7/13/2012 9:48	7/13/2012 9:48
Customer 924	Post article 17 Oct 2012	Louis Michel, Vincent Girardin, Pegau, Vieille Julienne, La Spinetta, Roberto Voerzio, Castello del Terriccio, Le Macchiole	10/17/2012 16:40	10/17/2012 16:40
Customer 956		Clos de Tart (new sign-ups will be Wait List), Louis Michel, Vincent Girardin, Gourt de Mautens, M&S Ogier, Pegau, Vieille Julienne, Borgogno, E. Pira - Chiara Boschis, La Spinetta, Massolino, Pelissero, Roberto Voerzio, Castello dei Rampolla, Castello del Terriccio, Ciacci Piccolomini, Fontodi, Il Carnasciale, La Massa, Le Macchiole, VinConnect Special Offers	11/13/2012 7:26	11/13/2012 7:26

Source: Company documents.

Exhibit 3

VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

VinConnect, Inc., AdWords Campaigns and Keywords

Campaign	Visits	Pages / Visit	Avg. Visit Duration	% New Visits
La Spinetta	152	3.66	0:01:25	87.50%
Ciacci Piccolomini	108	3.68	0:00:36	87.96%
Fontodi	82	2.78	0:00:23	90.24%
Borgogno	80	3.5	0:00:56	91.25%
Pegau	78	3.58	0:02:00	78.21%
Massolino - Google Build	68	3.82	0:01:01	83.82%
Clos de Tart	49	3.49	0:01:26	85.71%
Pelissero	49	2.71	0:09:29	81.63%
Castello dei Rampolla	44	4.64	0:03:04	65.91%
La Massa	40	3	0:00:36	87.50%
Le Macchiole	39	3.54	0:00:33	92.31%
Louis Michel	33	2.3	0:00:09	84.85%
Roberto Voerzio	24	2.96	0:00:26	83.33%
Ogier	21	3.81	0:01:45	80.95%
Chiara Boschis	13	5.08	0:02:30	92.31%
Vieille Julienne	11	2.18	0:00:03	81.82%
Castello del Terriccio	10	2.4	0:00:04	90.00%
(not set)	9	2.89	0:00:13	88.89%
Gourt de Mautens	8	3.5	0:01:01	100.00%

Keyword	Visits	Pages / Visit	Avg. Visit Duration	% New Visits
la spinetta	109	3.8	0:01:49	84.40%
ciacci piccolomini	92	3.82	0:00:37	86.96%
pegau	66	3.67	0:02:20	74.24%
borgogno	60	3.7	0:01:05	90.00%
massolino	55	3.42	0:00:55	83.64%
clos de tart	49	3.49	0:01:26	85.71%
castello dei rampolla	43	4.65	0:03:07	65.12%
la spinetta barbaresco	42	3.33	0:00:25	95.24%
le macchiole	39	3.54	0:00:33	92.31%
pelissero	37	2.84	0:12:32	83.78%
fontodi	32	2.56	0:00:21	93.75%
louis michel chablis	31	2.26	0:00:05	83.87%
la massa wine	23	3.39	0:00:54	86.96%
(content targeting)	21	2.1	0:00:17	95.24%
borgogno barolo	20	2.9	0:00:27	95.00%
ogier	18	4.11	0:02:02	77.78%
fontodi wine	17	4	0:00:32	88.24%
fontodi chianti	16	2.62	0:00:21	75.00%
ciacci piccolomini wine	13	3.08	0:00:40	100.00%
la massa	13	2.31	0:00:02	92.31%
massolino barolo	13	5.54	0:01:25	84.62%
domaine du pegau	12	3.08	0:00:13	100.00%
pelissero barbaresco	11	2.36	0:00:04	72.73%
roberto voerzio	11	4	0:00:52	72.73%
castello del terriccio	10	2.4	0:00:04	90.00%
voerzio	10	2	0:00:00	90.00%
(not set)	9	2.89	0:00:13	88.89%
chiara boschis	8	5.25	0:03:31	87.50%
vieille julienne	8	2.25	0:00:04	75.00%
gourt de mautens	7	3.71	0:01:10	100.00%
chiara boschis barolo	4	2.5	0:00:10	100.00%
fattoria la massa	4	3	0:00:43	75.00%
domaine de la vieille julienne	3	2	0:00:00	100.00%
ogier cote rotie	3	2	0:00:00	100.00%
roberto voerzio barolo	3	2.33	0:00:12	100.00%
domaine louis michel	2	3	0:01:03	100.00%
castello dei rampolla chianti	1	4	0:00:51	100.00%
e. pira chiara boschis	1	14	0:03:42	100.00%
gourt de mautens rasteau	1	2	0:00:00	100.00%
la spinetta barolo	1	2	0:00:00	100.00%

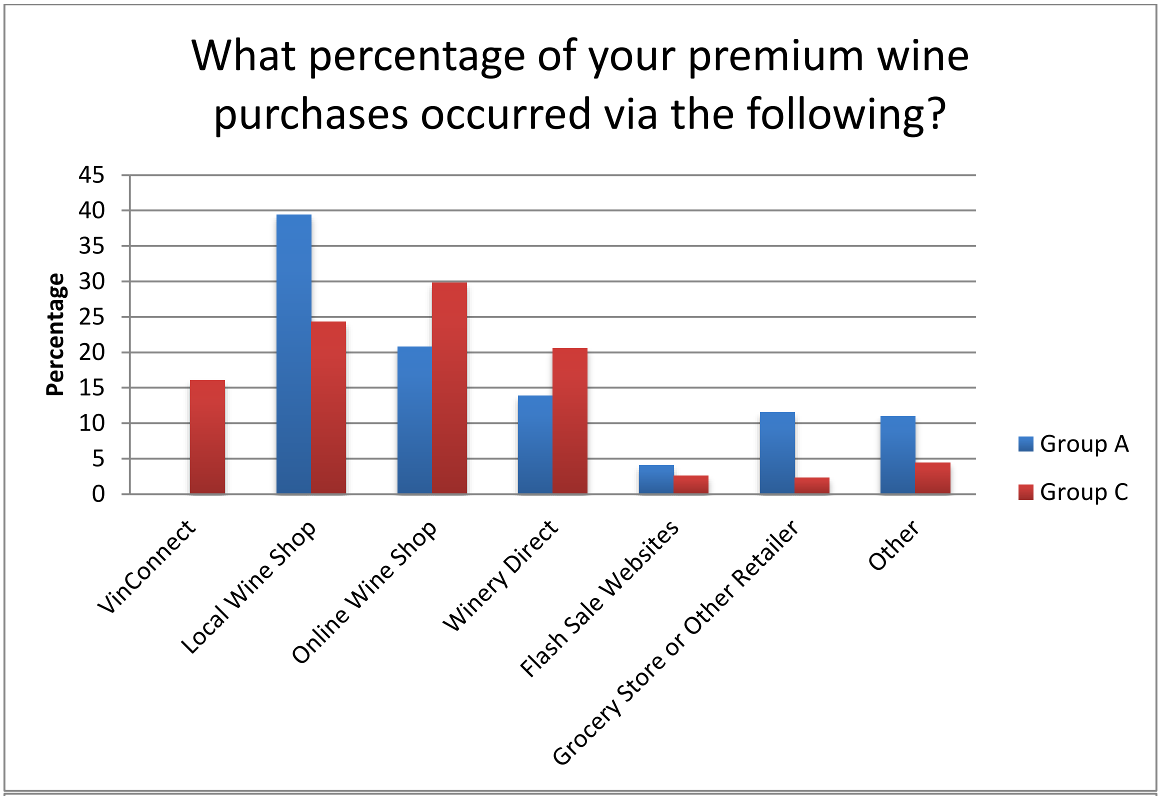
Matched Search Query	Visits	Pages / Visit	Avg. Visit Duration	% New Visits
la spinetta	37	5.05	0:04:21	78.38%
(not set)	30	2.33	0:00:15	93.33%
ciacci piccolomini	24	3.25	0:00:28	75.00%
clos de tart	24	3.79	0:02:21	87.50%
castello dei rampolla	16	6	0:07:13	43.75%
massolino	14	4.29	0:01:32	78.57%
borgogno barolo	13	2.77	0:00:15	92.31%
ciacci piccolomini d aragona 2009	12	3	0:00:33	91.67%
clos pegau	12	3	0:00:30	0.00%
le macchiole	12	4.33	0:00:41	75.00%
fontodi	11	2.36	0:00:08	100.00%
domaine du pegau	9	4	0:00:47	100.00%
la massa wine	8	3.25	0:00:20	75.00%
pelissero	8	3.5	0:00:57	100.00%
barolo borgogno	7	3.71	0:01:10	71.43%
ciacci piccolomini d aragona 2006	7	2.29	0:00:13	71.43%
ogier	7	3.71	0:02:09	57.14%
borgogno	6	6	0:05:14	100.00%
fontodi chianti	6	3	0:00:49	83.33%
louis michel chablis	6	2	0:00:00	100.00%
fontodi winery	5	7.2	0:01:26	100.00%
massolino barolo	5	10.8	0:02:51	60.00%
pegau	5	2.8	0:03:13	80.00%
pelissero wine	5	2	0:00:00	80.00%
borgogno langhe nebbiolo 2009	4	2.5	0:00:06	75.00%
ciacci piccolomini d aragona brunello d	4	2	0:00:00	100.00%
gourt de mautens	4	5	0:02:02	100.00%
la massa winery italy	4	7.5	0:04:30	100.00%
la spinetta barbaresco	4	2	0:00:00	75.00%
la spinetta moscato	4	4.5	0:00:47	100.00%
la spinetta moscato d asti bricco quagl	4	3.5	0:01:34	100.00%
moscato d asti la spinetta	4	5.5	0:00:51	75.00%
pelissero barbaresco	4	3	0:00:11	50.00%
roberto voerzio winery	4	5	0:01:55	25.00%
spinetta winery	4	3	0:00:25	100.00%
2007 castello dei rampolla vigna d alce	3	6.67	0:02:42	33.33%
castello dei rampolla sammarco	3	2	0:00:00	100.00%
castello del terriccio	3	2	0:00:00	100.00%
ciacci piccolomini d aragona 2007	3	4.67	0:00:31	100.00%
domaine pegau	3	2	0:00:00	66.67%
fontodi chianti classico	3	2	0:00:00	66.67%
fontodi wines	3	2.67	0:00:07	100.00%
la massa winery	3	2	0:00:00	66.67%
la spinetta moscato d asti	3	3.33	0:00:07	100.00%
la spinetta moscato d asti 2011	3	2	0:00:00	100.00%
la spinetta vermentino	3	3.33	0:00:06	100.00%
la spinetta wine	3	2.67	0:00:14	100.00%
le macchiole paleo	3	3.33	0:01:07	100.00%
massolino barolo 2007	3	2.67	0:01:23	100.00%
massolino parafada barolo	3	5.33	0:04:21	0.00%
pelissero barbera d alba piani	3	3	2:30:26	33.33%
plan pegau lot 2009	3	2	0:00:00	100.00%
roberto voerzio	3	4.67	0:00:35	100.00%
1990 castello dei rampolla sammarco t	2	4	0:00:52	50.00%
2 btl voerzio barolo la serra 2007	2	2	0:00:00	50.00%
2006 massolino margheria barolo	2	3	0:00:23	100.00%
barolo massolino	2	4	0:00:41	100.00%
barolo massolino 2000	2	2	0:00:00	50.00%
barolo massolino 2005	2	2	0:00:00	100.00%
borgogno barbera d alba 2008	2	2	0:00:00	100.00%
borgogno barbera superior	2	2	0:00:00	50.00%

Source: Company documents.

Exhibit 4

VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

Relevant Survey Responses



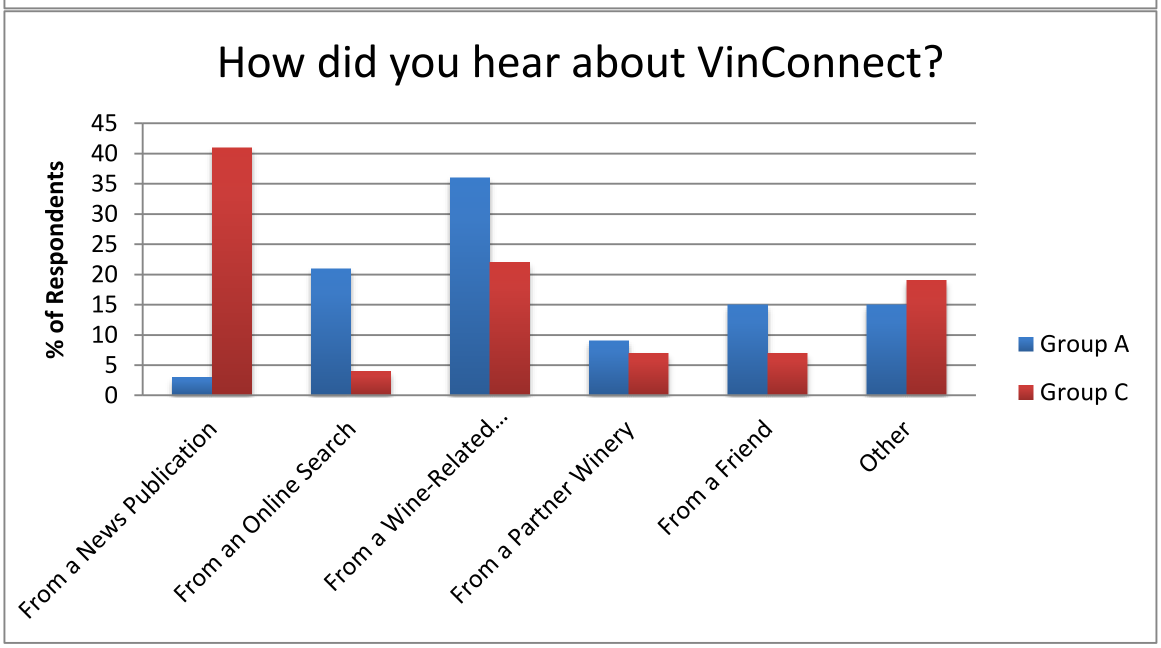


Exhibit 4 (continued)

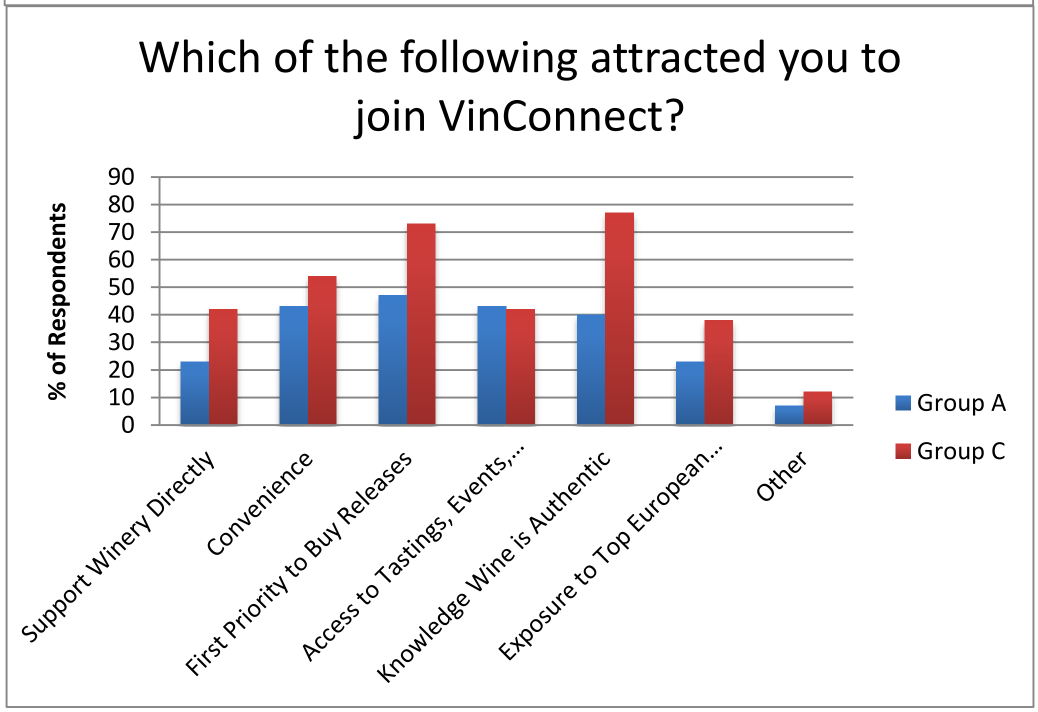
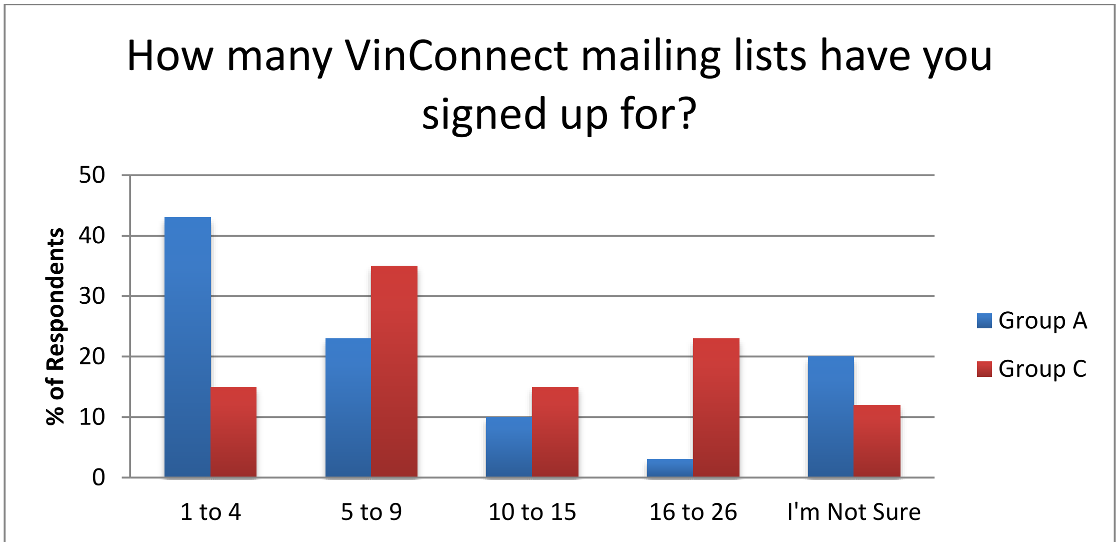
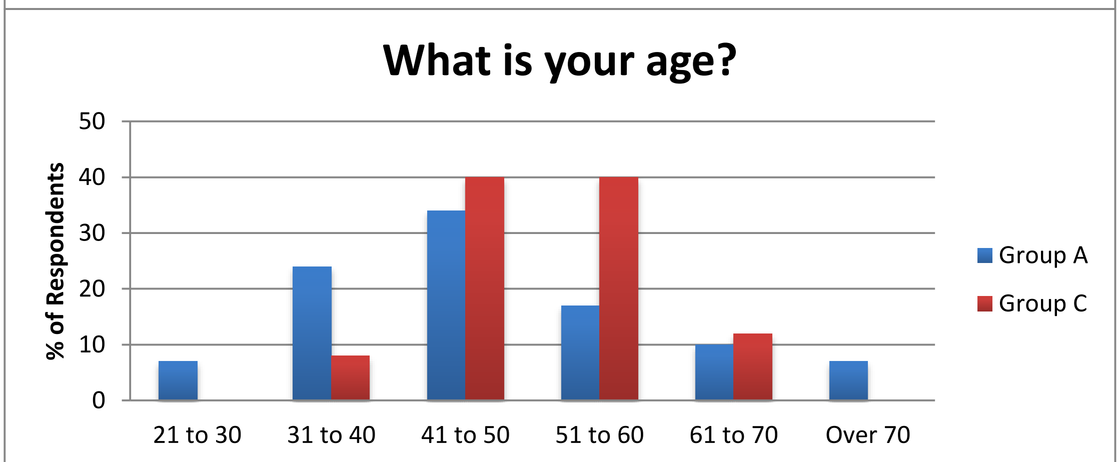
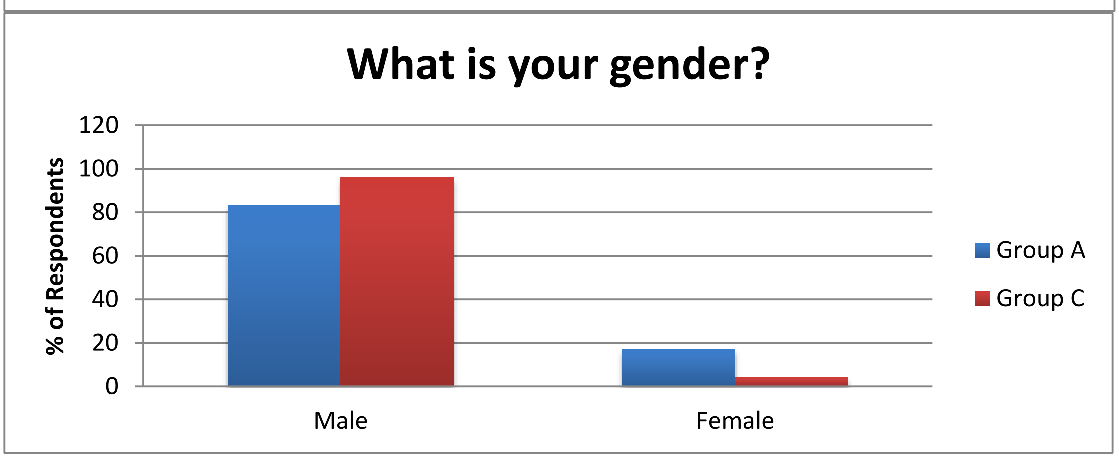


Exhibit 4 (continued)







Source: Company documents.

Exhibit 5

VINCONNECT, INC.: DIGITAL MARKETING STRATEGY

Total Website Visits by Date

Day	Visits
9/19/2011	11
9/20/2011	88
9/21/2011	61
9/22/2011	25
9/23/2011	9
9/24/2011	4
9/25/2011	7
9/26/2011	38
9/27/2011	29
9/28/2011	19
9/29/2011	16
9/30/2011	17
10/1/2011	5
10/2/2011	4
10/3/2011	18
10/4/2011	56
10/5/2011	37
10/6/2011	33
10/7/2011	17
10/8/2011	4
10/9/2011	5
10/10/2011	7
10/11/2011	15
10/12/2011	10
10/13/2011	11
10/14/2011	16
10/15/2011	24
10/16/2011	21
10/17/2011	30
10/18/2011	26
10/19/2011	14
10/20/2011	17

Source: Created by case writer.

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CARDAGIN: LOCAL MOBILE REWARDS

When you visit your favorite restaurant, the manager sometimes offers you a free dessert. The restaurant manager could provide such recognition for about 100 of their best customers, but what about the next 1,000 who are also regulars?

—Rob Masri

On a still-nippy February afternoon, Rob Masri, CEO of Cardagin, a mobile marketing network based in Charlottesville, Virginia, scanned his iPhone app as he entered Eppie's, a local restaurant. Through the Cardagin app, Eppie's, an early member of the Cardagin network, could track a user's visits and offer personalized coupons on the spot. That day, Masri was able to redeem a 90% discount for our lunch, over which he spoke passionately about Cardagin's fast progress, the decisions facing him, and the broader trends in mobile marketing.

Since its launch in September 2010, Cardagin had signed up more than 1,200 merchants in 30 cities over 20 states to offer loyalty programs through Cardagin's mobile app and raised over $5 million in venture funding. More than 25,000 customers had downloaded the Cardagin app, and the mayor of Charlottesville had declared January 18, 2011, Cardagin Day. It was a great start for a business that provided a mobile-phone platform for merchants to access their loyal customers and for customers to obtain personalized rewards from all their favorite merchants in a single location. (**Exhibits 1** and **2** provide an overview of Cardagin's initial launch growth and early user demographics.)

Masri recognized early on that using a smartphone as a marketing medium was an effective way to reach an increasingly mobile consumer base, and the initial challenge was convincing retailers of the value in reaching it. To do so, he would need to increase both the merchant and consumer networks, find new cities for the next expansion phase, and develop and price the next generation of services, helping merchants provide rewards for their customers that were personalized and effective. He had already identified a niche among smaller local businesses in college towns. A number of vendors were all simultaneously trying to capitalize on

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This case was prepared by Rajkumar Venkatesan, Bank of America Research Associate Professor of Business Administration, and Kelly Ateya, Research Assistant, with assistance from Adam Harr (MBA '11). It was written as a basis for class discussion rather than to illustrate effective or ineffective handling of an administrative situation.

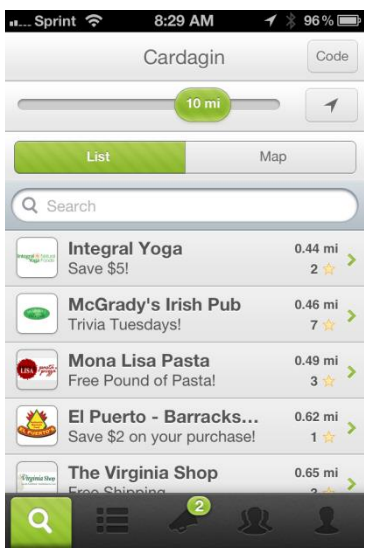
the mobile-coupon trends, so rapid expansion and effective couponing strategies were critical. (**Exhibit 3** is a case study used by Cardagin to educate prospective clients.)

Cardagin Network

By creating a mobile presence in Cardagin's mobile apps, local businesses had exclusive access to a modern customer-retention tool and could begin to identify, reward, and communicate with their best customers—the 20% who generated 80% of their revenue.

Cardagin created a network of local businesses (**Figure 1**). The larger the user base of consumers and merchants, the more valuable and beneficial the network. Using Cardagin's smartphone app, consumers could find their favorite local stores or explore new merchants, eliminating paper loyalty club cards and coupons by tracking and managing points and rewards on a smartphone instead. By accessing the merchant portal on Cardagin.com, merchants could create a mobile presence and target advertisements and promotions to those local consumers most likely to buy their services or products. Through Cardagin's mobile loyalty technology, local businesses could monitor customer spending habits and make more intelligent and better-informed marketing decisions.

Figure 1. Cardagin network.



Source: Cardagin. Used with permission.

The Cardagin software enabled a merchant to target a specific subset of a customer base at specific times. Offers and rewards could be created "on the fly" for immediate effect, with GPS or location-based features making it possible to create and distribute advertisements and promotions much faster and more directly than a traditional television or newspaper advertising channel.

The Cardagin platform had two main components:

- The *mobile app* allowed consumers to use their smartphones to browse businesses, view offers, redeem coupons, join groups, receive notifications, earn loyalty points, and collect rewards. Cardagin offered a native app for the iPhone and for Android-enabled phones, eliminating dependence on Internet availability, as well as a mobile website for BlackBerry, Windows Phone 7, and browser-enabled feature phones. In addition to the consumer features, Cardagin's iPhone app allowed businesses to record transactions and award points at the point of purchase. For example, a business manager could log into the Cardagin app, scan a customer's loyalty or redemption code, enter the purchase amount, and submit the transaction to be recorded on Cardagin's servers.
- The *Cardagin.com website* provided a self-service merchant portal for a business to easily manage its Cardagin account. Businesses could input location information (address, phone number, website, etc.); create advertisements, offers, and rewards; and track loyalty data and other metrics. Additionally, businesses could use the merchant portal to record purchases and award loyalty points (in lieu of a scan or point-of-sale integration). While the main point of use for consumers was via the mobile app and website, Cardagin was in the process of developing a consumer web portal to allow users without smartphones to manage their loyalty points and rewards.

Cardagin gave local merchants an affordable alternative to traditional advertising. At a cost of $200 per month, or about $6.67 per day, many local merchants could afford to enter the mobile marketing space. Cost differences as compared to traditional sources are outlined in **Table 1**.

Table 1. Traditional advertising costs by source and size.[1]

Yellow pages	Half-page ad	$6,000/year
Newspaper (25,000 circulation)	Quarter-page ad	$300/day
Radio spot	30-second	$50/spot
TV spot	30-second	$60/spot
Direct mail	Flyer	$1,000/month

Data source: Case writer estimates based on Charlottesville advertising market.

Once published, the advertisement or reward on the Cardagin app remained active until the merchant changed it, whereas most traditional channels charged for every rerun of the advertisement. Furthermore, these promotions could be more targeted than newspaper or television ads, and the retailer had no obligation to share any earned revenues from deals or points redeemed.

[1] Advertisements in many of these channels had to be run multiple times in order to be effective.

The Pilot

To test the Cardagin concept in the marketplace, a two-part pilot program with a small sample (<10) of local businesses based in Charlottesville, Virginia, was conducted in the fall of 2010, during which participating merchants were provided Cardagin services free of charge. Merchant feedback suggested a need to tier the services by including a low-cost, entry-level product that allowed them to "dip their toes" into the mobile-advertising waters.

The firm responded with *Cardagin Broadcast*, which provided limited mobile advertising and tracking, and *Cardagin Complete*, a full-service mobile loyalty component, consumer demographics, coupon redemption rates, and other data tracking. Differences between these products are highlighted in **Table 2**.

Table 2. The Cardagin product line.

	Cardagin Broadcast	Cardagin Complete
Mobile ads	✓	✓
Access to Cardagin network	✓	✓
Track promotional views	✓	✓
Mobile loyalty program		✓
Track purchases and redemptions		✓
Targeted ads		✓
Access to reporting center		✓

Data source: Cardagin. Used with permission.

For retail clients to be willing to upgrade to full service, Masri would need to demonstrate the value of mobile marketing as a customer acquisition and retention tool. Mobile marketing garnered more data than traditional marketing activity, so a retailer could build a CRM (customer relationship management) database, enabling it to use customers' past behavior to devise tactical mobile-marketing campaigns to attract repeat purchases.[2]

A second pilot in the first half of 2011 expanded outside of Charlottesville—to Northern Virginia and southern Pennsylvania, as well as Blacksburg, Virginia; Nashville, Tennessee; and Fort Worth, Texas. The second pilot tested three concepts: (1) proof of concept in non–college town markets, (2) consumer adoption of the Cardagin mobile app, and (3) market need and demand for a local mobile-advertising outlet (with and without the loyalty component). On the consumer front, the Cardagin website was launched, and the free iPhone and Android apps were released to the public. During this period, more than 400 businesses signed up and nearly 6,000 users created new accounts. Based on the first pilot, the case writers estimated the retention rate of merchants ranged from 75% to 89%. Usage data revealed that merchants who remained with the Cardagin network boasted higher penetration rates with Cardagin's user base (with 285 active users for retained merchants versus 21 active users for churned merchants) and more transactions per user (1,210 versus 58).

[2] Ariya Priyasantha, "How to Harness the Power of Mobile Couponing," Mobile Marketer, July 20, 2010, http://www.mobilemarketer.com/cms/opinion/columns/6809.html (accessed Oct. 12, 2011).

Each merchant on Cardagin provided at least one daily advertisement for consumers to view and redeem. Ads varied greatly among businesses. Many merchants provided a general-broadcast type of coupon, such as 10% off any product for two weeks or more, while others provided more personalized coupons for their best customers: buy one, get one 50% off, free state inspection with purchase of an oil change, or $2.00 off a lunch buffet. During this initial period, redemption information was not collected.

A new platform released in July 2011 could account for consumer redemptions based on consumer clicks, but it still could not verify if a click resulted in actual usage until businesses upgraded to the new loyalty component. At that level of service, data could be captured directly from a consumer's phone, either by scanning a quick response (QR) code or by the cashier manually entering a 10-digit alphanumeric code or the customer's mobile number.

Merchant portal

Key for retailers was the user-friendly merchant portal, a self-service mobile-marketing platform that allowed them to easily create, edit, and track offers and loyalty programs. After logging into the portal, merchants could review business details and advertisements across multiple locations and easily manage their mobile advertising and loyalty programs (**Exhibit 4a**).

Following the execution of a promotion, merchants could use the portal to track coupon usage and customer loyalty metrics such as redemption rates and followers (**Exhibit 4b**). Self-sufficiency among retailers was the end goal, but as part of the firm's value proposition, customer service support would be required, initially in 100 markets across the United States.

Consumer app

Once consumers downloaded the Cardagin app, they could search for participating merchants by name, zip code, or locations nearest to them. Promotions provided by a merchant were then visible (**Figure 2a**). Clicking on a promotion brought up a barcode (**Figure 2b**) that could be scanned by the merchant's data capture device, which could be an iPhone or iPod Touch, to redeem the reward.

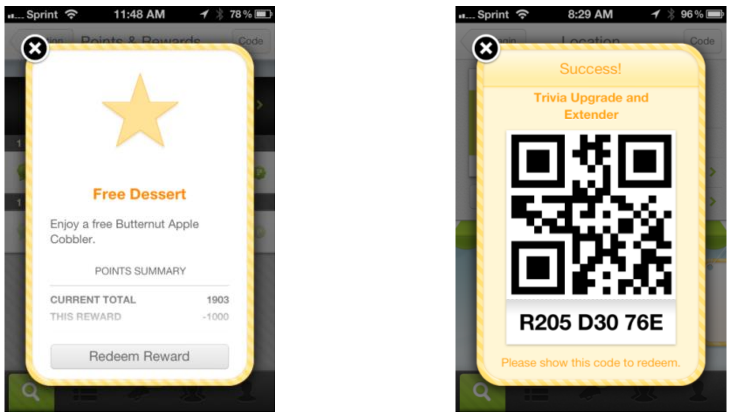
Merchant network

An important aspect of Cardagin's value proposition was the possibility of a merchant network (**Exhibit 5a**). By aggregating within a specific geographic area under the Cardagin banner, merchants could not only reward and retain existing customers but also acquire new customers via network partners.

Masri focused his efforts on college towns, using a grassroots campaign fostered by a brokered sales force. The college-town locale provided access to a younger consumer base and single-location merchants underserved by national providers. Masri also approached university alumni and athletics associations with the Cardagin solution and offered those groups the option of providing exclusive offers for their members from merchants in the Cardagin network. For the merchants, Cardagin provided a way to access members of a lucrative but elusive group. (**Exhibit 5** provides an overview of Cardagin services.)

Figure 2. The Cardagin app consumer's view.

2a. Sample Reward 2b. Redemption Screen



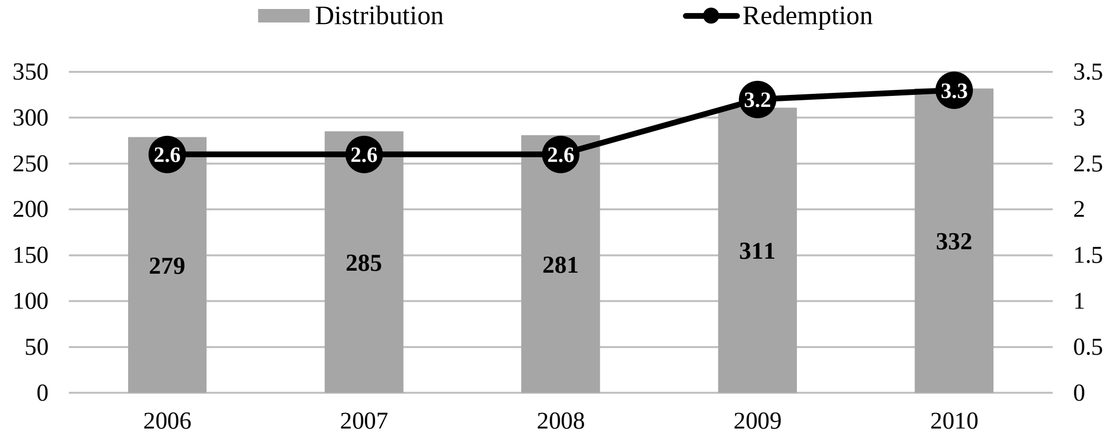
Source: Cardagin. Used with permission.

Competition

Printed coupons

During the economic recession of 2008–09, U.S. annual coupon usage increased for the first time since the early 1990s, and 2010 marked the largest single-year distribution quantity of consumer packaged goods (CPG) coupons ever recorded in the United States: 332 billion. Redemption peaked in 1999 at 4.6 billion, then averaged 2.6 billion between 2006 and 2008, rising again in 2009 and 2010 to 3.3 billion, representing consumer savings of an estimated $3.7 billion (**Figure 3**).

Figure 3. U.S. CPG coupon distribution and redemption volume (in billions).



Data sources: NCH Marketing Services, Inc., *Annual Topline U.S. CPG Coupon Facts Report for Year-end 2010;* Todd Hale, *The Coupon Comeback*, April 13, 2010, http://blog.nielsen.com/nielsenwire/consumer/the-coupon-comeback/ (accessed November 9, 2011).

Despite growth within all other classes of trade, conventional grocery stores still accounted for the highest coupon redemption rates (**Table 3**):

Table 3. Total coupon redemption volume by retail channel (in percent).

	2008	**2009**	**2010**
Grocery stores	59.9	60.6	59.7
Mass merchandisers	25.0	24.4	23.9
Drug stores	6.5	6.2	6.6
Military commissaries	4.9	4.2	4.1
Other[3]	3.9	4.6	5.7

Data source: NCH Marketing Services, Inc., *Coupon Facts Report 2011*.

Newspaper inserts remained the primary method for the distribution (89%) and redemption (53%) of coupons, but with more and more consumers making digital coupons part of their shopping routine and more than $1.2 billion in savings issued in 2010, the digital coupon market dramatically outpaced the growth of newspaper coupons by approximately 6 to 1.[4] While online coupons represented only 1% of overall coupon distribution, they had grown to nearly 10% of redemptions in 2009 and had been the industry growth engine in recent years.[5] Other paperless coupon distribution methods, such as electronic checkout (39%), digital promotions (31%), and tear pads (30%), also helped drive 2009's significant growth in coupon redemptions (**Table 4**):[6]

[3] Includes convenience stores, warehouses/clubs, and variety/discount stores (such as the Dollar Store).

[4] Kantar Media press release, January 5, 2011.

[5] Jack Neff, "Coupon Clipping Stages a Comeback," *Advertising Age*, November 1, 2010, http://adage.com/article/news/newspaper-print-coupon-clipping-stages-a-comeback/146816.

[6] Todd Hale, "The Coupon Comeback," Nielsen, April 13, 2010, http://www.nielsen.com/us/en/newswire/2010/the-coupon-comeback.html.

Table 4. Total coupon distribution volume by media type (in percent).

	2009	**2010**
Free-standing insert (FSI)	85.9	87.7
All other media	14.1	12.3
In-store handout	5.6	5.2
Direct mail	2.6	2.4
Magazine	2.4	2.2
In/on pack and cross-ruff[7]	1.4	1.1
Other[8]	2.1	< 2.0

Data source: NCH Marketing Services, Inc., *Coupon Facts Report 2011*.

Four sustainable trends were likely driving the rapid shift in coupon redemption: (1) dramatic global penetration of mobile devices and media (e.g., smartphones, tablets, QR codes, location-based services), (2) social media fueling changes in consumption patterns, (3) retailer recognition and active participation in mobile couponing (e.g., linking consumer to loyalty card data, personalization of coupons and rewards), and (4) the promising future of mobile wallets, which allowed consumers to carry the contents of a wallet on a phone (e.g., credit/debit card, coupons, shopping lists).

Daily deals

Groupon was the largest and fastest-growing firm in the group buying space, and its daily deal service provided more than 50% of its sales revenue. Like Cardagin, Groupon's value proposition also centered on giving local firms access to local markets, although Groupon sought to leverage the vast network of consumers registered to its service and to drive customer acquisition to local businesses. Cardagin's focus was on customer retention and building customer loyalty. Groupon's payment model was also different. Groupon collected a prepayment from the consumer and then paid the merchant a percentage of that payment; Cardagin did not sell coupons to consumers and received no shared revenue. Instead, Cardagin relied on monthly subscription fees paid by the businesses.

With a surplus supply of deals and low barriers to entry, it was expected that competition within the industry would grow quickly. Through its acquisition of Punchd, a customer loyalty program based on the "buy-10-get-1-free" punch-card system, Google fueled speculation that it was adding a loyalty component to its checkout product, Google Wallet. AT&T was planning to enter the market through Yellowpages.com.[9] Amazon.com had invested in LivingSocial. Yelp.com, the restaurant review site, considered creating its own version of daily deals.

[7] A *cross-ruff* coupon is distributed as part of a product's packaging but is only redeemable for future purchases.
[8] Includes newspapers, digital/online, and handouts away from store.
[9] Kris Ashton, "AT&T to Offer Deals on Its YP.com Site," Daily Deal Media, May 2, 2011, http://www.dailydealmedia.com/369att-to-offer-deals-on-its-yp-com-site/ (accessed Oct. 13, 2011).

Mobile coupons

Companies such as Coupon Rover, Coupons.com, Yowza!!, and Coupon Sherpa provided coupons on mobile apps, but the majority were focused on national brand stores and not local merchants. Mobile applications provided by Foursquare, SCVNGR, and Gowalla capitalized on the trend in social games, allowing people to check in at certain locations and earn rewards or go on scavenger hunts and play games with customers. Location services such as Placepop allowed consumers to check in when they visited a merchant and redeem offers based on frequency. Placepop in particular also allowed users to suggest rewards and create unique loyalty programs with the merchants directly.

Mobile loyalty companies such as Sundrop, Punchd, and PlumReward were the most similar to Cardagin. They provided loyalty solutions to help retain customers but no customer acquisition package. Cardstar, KeyRing, and CardKing provided consumers with a way to store the plastic cards and key fobs of local and national businesses on their mobile phones, but they did not create the loyalty programs for those businesses nor did they store information on a customer's transaction. Industry analysts believed that the ability to provide relevant consumer information to merchants would determine which services survived long-term.[10]

Decisions

Cardagin received positive reviews from local television, social media, industry blogs, and entrepreneurship magazines, including TechCrunch, *Inc.* magazine, CNET, and VentureBeat. What remained for Masri was to develop a simple yet convincing comparison of costs and returns between Cardagin and traditional local channels. What kinds of promotions were more effective for which consumers and when?

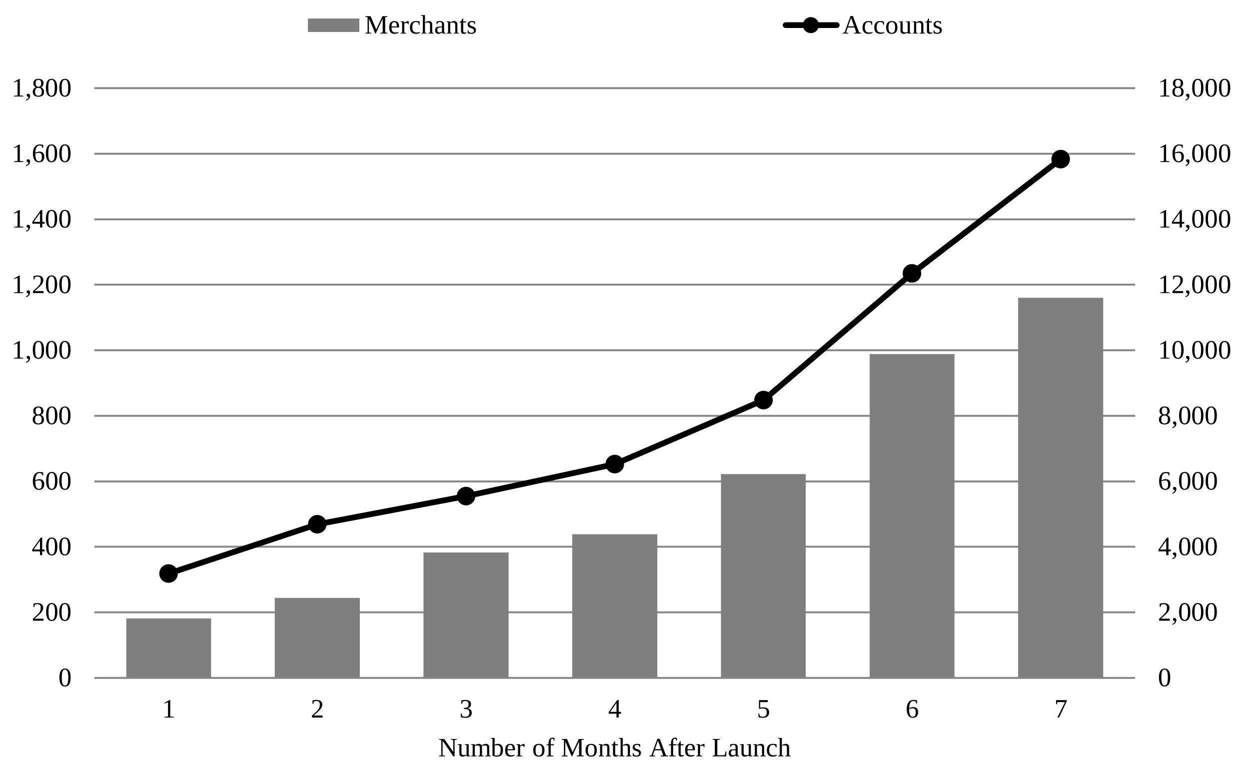
Masri had to prioritize his marketing spending. Should he focus on acquiring new merchants or retaining existing ones? How much could Masri spend on acquiring a new merchant? What was the value of a single merchant to Cardagin's network? He wondered if the size of the existing merchant network helped him attract new merchants and consumers to the Cardagin platform, and how he could quantify this positive network effect. How can the data from Cardagin's network inform his decisions?

[10] Issie Lapowsky, "Horse Race: No Hole Punch Required," *Inc.*, November 2010.

Exhibit 1

CARDAGIN: LOCAL MOBILE REWARDS

Cardagin Growth in Numbers of Merchants (left axis) and Accounts (right axis)



Data source: Cardagin. Used with permission.

Exhibit 2

CARDAGIN: LOCAL MOBILE REWARDS

Key Metrics for Cardagin Users

Age	
< 18	0.9%
18–24	17.5%
25–34	30.8%
35–44	25.2%
> 45	25.5%
Education	
High School	10.0%
Associate's Degree	6.7%
Bachelor's Degree	50.0%
Graduate Degree	21.7%
Postgraduate Degree	11.6%
Marital Status	
Married	50.2%
Single	45.1%
Divorced	4.8%
Gender	
Male	46.4%
Female	53.6%

Data source: Cardagin, based on demographic information obtained during customer registration of version 1.0; such information was no longer required in subsequent versions.

Exhibit 3

CARDAGIN: LOCAL MOBILE REWARDS

Overview of Cardagin Services for Prospective Clients

Cardagin
Case Study

www.cardagin.com

The Local Merchant

A local coffee and donut franchise in Charlottesville, VA struggled with coupons and paper punch cards for years. Andy, the local franchise owner, spent on average $12,000 per year to attract customers to his store with limited success.

Andy wanted to learn more about his customers - who used coupons, who picked up punch cards and who spent what? He chose Cardagin for his marketing and customer retention needs.

> *"Using Cardagin, we acquired a group of customers who want to hear from us, who care about us and who respond to our offers."*
> *Andy, local franchise owner*

The Setup

Andy worked with Cardagin to devise a multi-part mobile marketing campaign targeting University of Virginia students. As the students returned from summer break, Andy offered an exclusive promotion that could only be redeemed through Cardagin: "**any** drink, **any** size for **free**!" This exclusive offer ran for one week and was designed to attract customers to Andy's store and join his loyalty program, powered by Cardagin.

The following two weeks, Andy ran another exclusive offer on Cardagin: "**any** drink, **any** size for **$0.99**!" This offer, while still aggressive, helped Andy engage his new customers on his new platform. During the final two weeks of his mobile campaign, Andy ran a final offer: "**any** drink, **any** size for **$1.19**!" As customers redeemed the offer, Andy encouraged his staff to remind every customer to join his mobile loyalty program and earn points for every dollar they spend.

> ***Marketing Tip***
> *Having staff encourage all customers to join your new loyalty program, powered by Cardagin, gives you insight into the value of a customer.*

The Results

So, what happened? As a result of creative marketing and using Cardagin's unique mobile technology, Andy was able to generate substantial revenue for his business. More importantly, Andy's new loyalty program, powered by Cardagin, generated repeat customers instead of one-time deal hunters, and gave Andy insight into a group of customers that he can engage and reach at anytime. Here's a look at the numbers:

Redemptions: **How many drink offers were redeemed?**

- Free drink offer: 531 in one week
- $0.99 drink offer: 329 in first week, 268 in second week
- $1.19 drink offer: 231 in first week, 184 in second week

Short-Term Gain: **What was the immediate impact of the campaign?**

- Campaign revenue: $1,084.88 (excluding additional purchases)
- Hundreds of new customers within a specific demographic
- Upsell opportunities of higher margin items

Long-Term Gain: **What were the long-term benefits of the campaign?**

- Repeat customers who are rewarded for their loyalty
- Direct line of communication with engaged customers
- Transaction log of who spent what, when and where
- Viral marketing from loyal customers who share savings and rewards via social media outlets and who recommend Andy's business to their friends and family

The Bottom Line

Cardagin helps Andy identify his best customers. He now knows that Karen R., Richard G. and Matt S. come in everyday for their morning coffee. The lifetime value of these customers, and others like them, is priceless to a local business. Using Cardagin, Andy has a modern, meaningful and cost-effective way to reach, engage, reward and retain those customers who mean the most to his business.

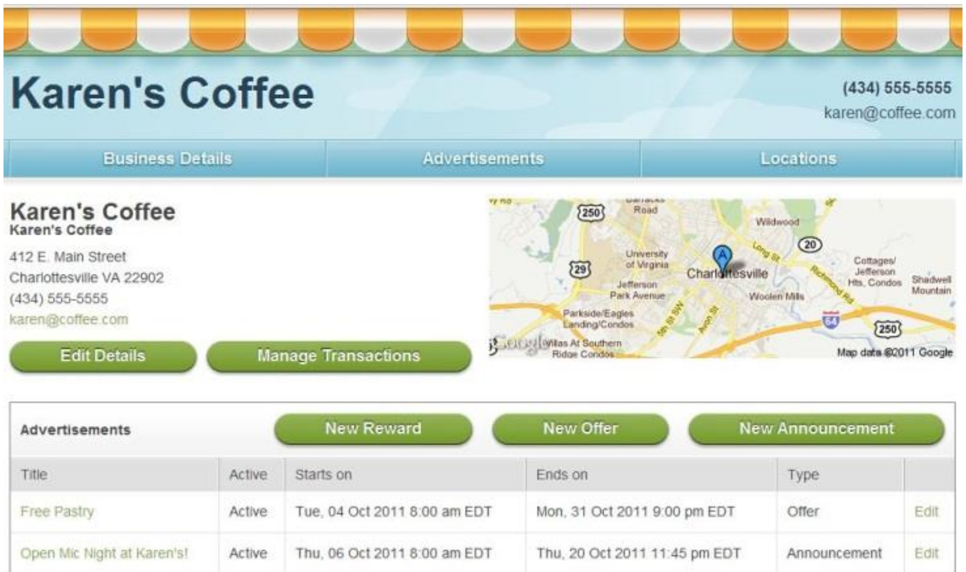
Source: Cardagin. Used with permission.

Exhibit 4

CARDAGIN: LOCAL MOBILE REWARDS

The Cardagin Merchant Portal

4a. Merchant Portal



4b. Information Reporting

Source: Cardagin. Used with permission.

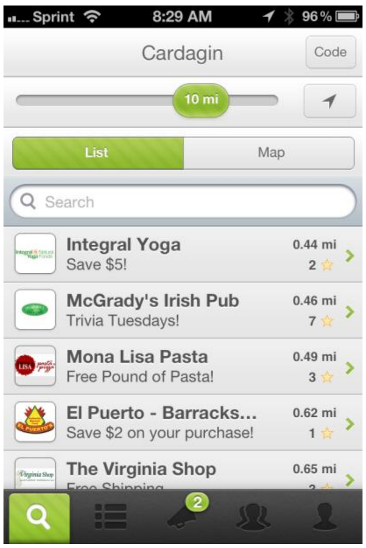
Exhibit 5

CARDAGIN: LOCAL MOBILE REWARDS

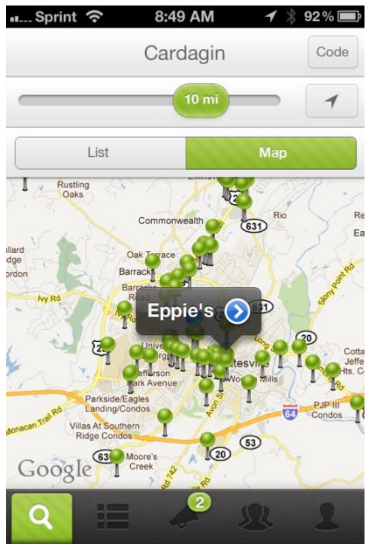
Overview of Cardagin Services for Eppie's Restaurant

Network Effect of Being Listed with Other Local Businesses

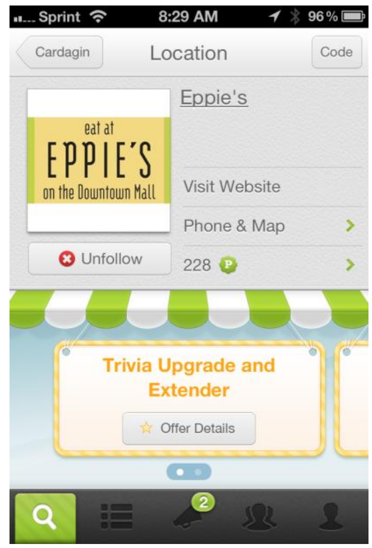
5a. List View



5b. Map View

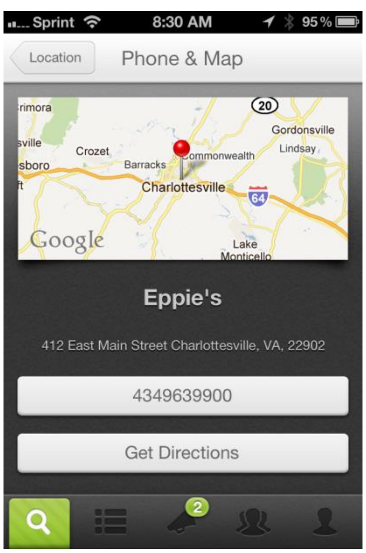


5c. Business Storefront

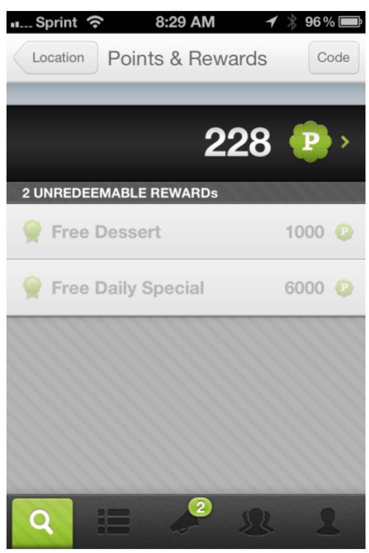


Mobile Presence in Cardagin

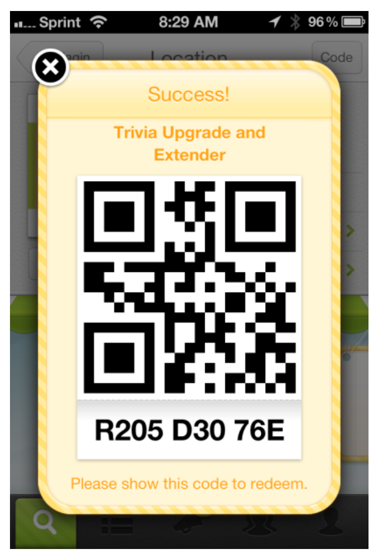
5d. Business Information



5e. Points Screen



5f. Redemption Screen



Source: Cardagin. Used with permission.

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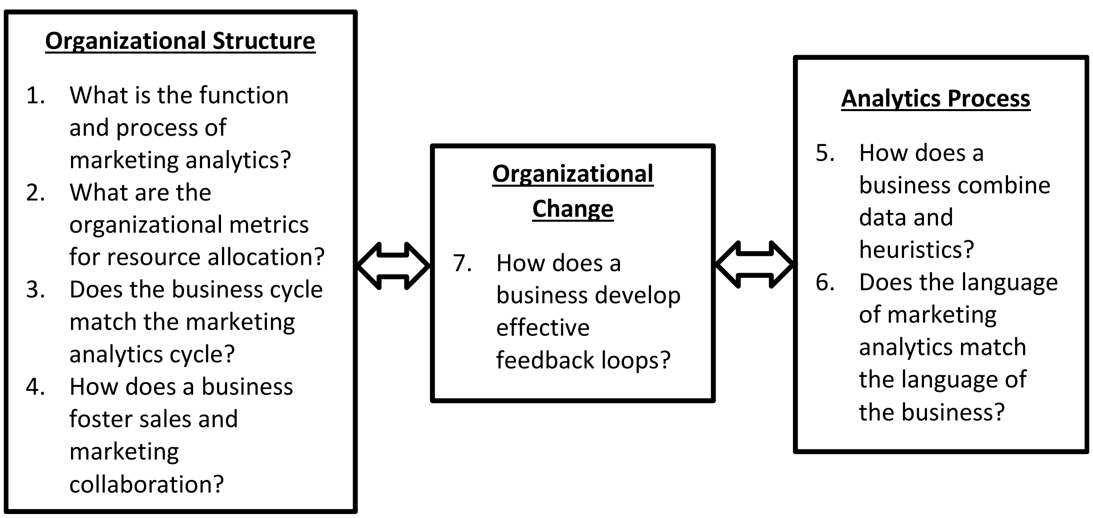
IMPLEMENTING MARKETING ANALYTICS

Marketing analytics powered by "big data" holds the promise to shift marketing strategy from an intuitive discipline to a fact-based decision-making process. Despite its potential, widespread adoption of marketing analytics within organizations remains a challenge. The following road map for improving implementation of marketing analytics is based on our interactions with more than 100 executives in conferences, executive education seminars, case study development, and consulting projects.

The starting point for implementation of marketing analytics is top management support and the integration of the marketing analytics function in business processes. Given this launching pad, firms must address issues related to organizational structures, analytics processes, and organizational change to foster implementation of analytics (**Figure 1**). Within this framework, managers should ask seven key questions to start the journey toward a marketing analytics–driven culture.

Figure 1. Road map for implementing marketing analytics.



Source: All figures created by case writer.

This technical note was prepared by Paul W. Farris, Landmark Communications Professor of Business Administration, and Rajkumar Venkatesan, Bank of America Research Professor of Business Administration.

Organizational Structure

What is the function and process of marketing analytics?

The objective of marketing analytics is to shift from intuition-based to fact-based decision making. It is important to understand that effective marketing analytics entails a combination of attribution of sales to different marketing mediums, optimization, and allocation of marketing resources; accounting for consumer response (including search, online chatter, store visits, and purchasing behavior); and business outcomes (including unit sales, revenues, market share, and customer lifetime value). Without taking such a holistic approach and considering market conditions and competitive activities, organizations cannot see the full effect of marketing, and this leads to a gap in the credibility of marketing analytics.

Field experiments are the first step in taking action on the recommendations of marketing analytics. A test-and-learn environment is essential for this adoption. However, in reality, ongoing tests of media budgets are possible only in the presence of fluid marketing and media management. Often, budgets are allocated to specific media types, but a holistic perspective allows for flexibility across media vehicles. Marketing analytics professionals, on the other hand, need to understand the organizational culture and capabilities of data and IT systems.

Even if an organization develops a holistic analytics function and provides fluid budgets to media vehicles, and the analytics professionals are embedded within the organization's systems and culture, management's need for control may lead it to reject models. A way around this is to customize models for managers and train them on how to use and understand them.[1] Simulation software and scenario planning are, therefore, essential for implementation of analytics. Analytics professionals need to recognize the limits of the models underlying their predictions and recommendations. Simulation software that lets managers change the business parameters or assumptions and evaluate consequences would go a long way toward developing comfort with analytics among managers.

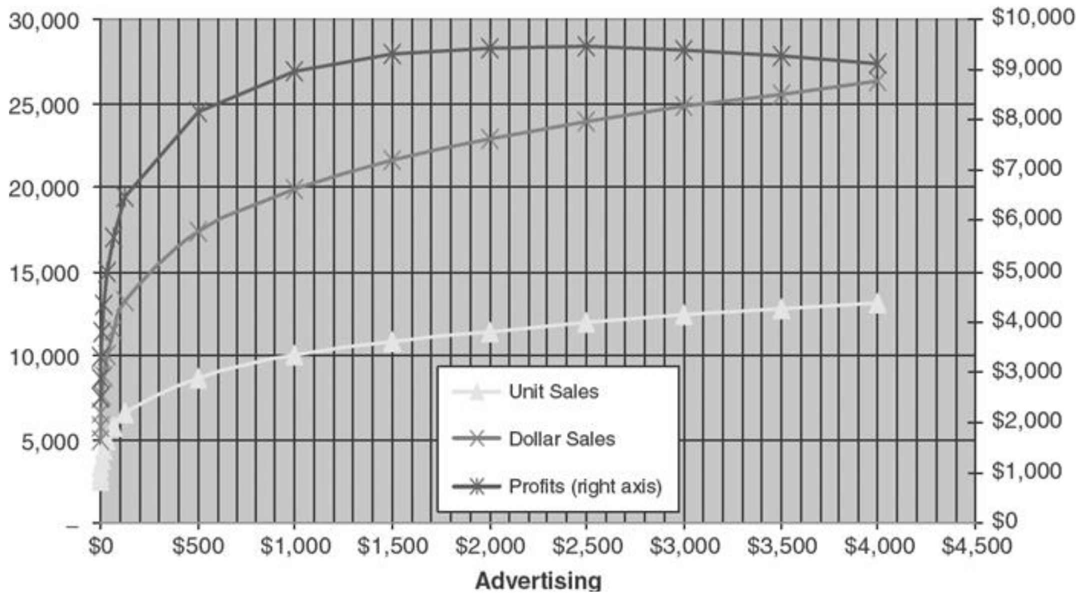
What are the organizational metrics for resource allocation?

Successful implementation of the budgeting process necessitates focusing on better allocation rather than on total budget optimization. Profit functions typically have a flat maximum (**Figure 2**). In other words, it is typical to find that net profit does not increase after a certain level of marketing spending, even if unit sales continue to increase with marketing spend.

Managers are, therefore, better off not optimizing the total budget but rather focusing on reallocating resources across media channels for a fixed budget.

[1] Gary L. Lilien, Arvind Rangaswamy, Gerrit H. Van Bruggen, and Katrin Starke, "DSS Effectiveness in Marketing Resource Allocation Decisions: Reality vs. Perception," *Information Systems Research* 15, no. 3 (2004): 216–35.

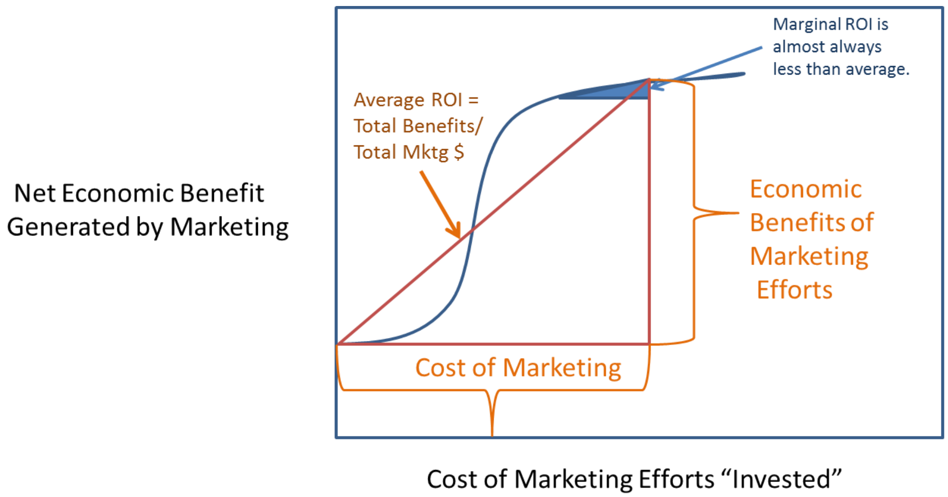
Figure 2. The flat maximum principle of profits.



It is important that organizations decide the metrics for evaluating the effectiveness of marketing spending up front and share those metrics widely. It is best to use a wide range of metrics to evaluate marketing investments. Return on investment (ROI) is, however, the most common metric in assessing the value of marketing tools because it is easiest to use in analytical marketing-mix models. Optimization recommendations that use ROI to a large extent recommend reduction of marketing budgets because the returns from marketing investments are not linear, as is typical in many capital projects. Market response functions typically follow an S-shaped curve (**Figure 3**), where small investments in marketing do not lead to sales response. Beyond a certain threshold, incremental marketing investments start providing returns. Beyond an upper limit, however, additional investments do not lead to a corresponding increase in sales. Such an S-shaped function takes into account typical marketing phenomena such as diminishing returns and long-term carry-over.

As shown in **Figure 3**, ROI calculations that are based on total returns and total marketing investments ignore where a brand is on the market response curve. The key is, therefore, to look at the return on marketing investment (ROMI), or the return on marginal investment.

Figure 3. Marketing ROI is not linear.



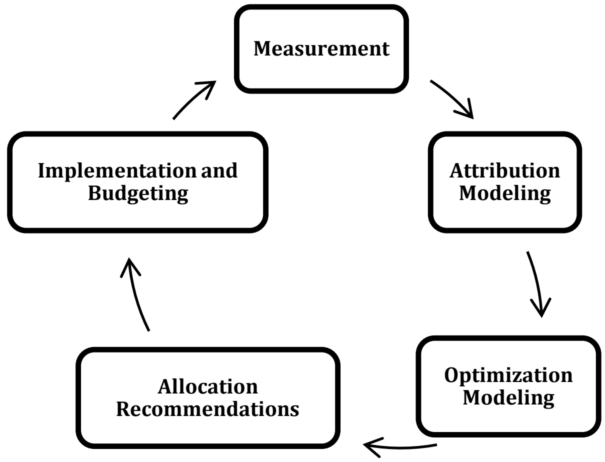
ROMI is calculated as a "contribution attributable to marketing (net of marketing spending), divided by the marketing 'invested' or risked."[2] The challenge with ROMI is identifying sales that are attributable to marketing. Marketing analytics and smart experimental designs can be very useful in identifying the lift in sales attributable to marketing investments. As shown in **Figure 3**, ROI is typically higher than ROMI. Optimization of marketing based on ROI would, therefore, normally recommend a lower investment in marketing than ROMI because ROI attributes all of a firm's sales to marketing investments. A ROMI-based strategy takes a more measured approach and accommodates nuances in consumer response to marketing.

Does the business cycle match the marketing analytics cycle?

The cadence of business and analytics decisions must be synchronized. For example, purchasing television spots in advance can provide greater discounts (sometimes as high as 50%) and provide structure for media planners and the sales force. But this forward-buying also establishes lock-in and comes at the expense of flexibility, which is often necessary for testing the effects of reallocations recommended by marketing analytics. It is, therefore, necessary to take into account media purchase cycles and synchronize the marketing analytics and sales force activities with this cycle. A proposed analytics and decision cycle is provided in **Figure 4**.

[2] Paul Farris, Neil Bendle, Phillip Pfeifer, and David Reibstein, *Marketing Metrics: The Definitive Guide to Measuring Marketing Performance*, 2nd ed. (Upper Saddle River, NJ: Pearson Business Publishing, 2010).

Figure 4. Synchronization of management budgeting and allocation cycles.



How does a business foster sales and marketing collaboration?

Technology developments (especially the Internet) have provided customers access to more information on products than ever before. In this environment, consumers are increasingly conducting their own research online before meeting the sales people, which changes the dynamics of a sales call. Salespeople, on the other hand, also have access to information on consumer behavior and can use technology to address customer queries real time during a sales call. Marketing can develop insights on customer behavior, which can help the sales force by providing better-quality and more leads.

Organizations, therefore, need a unified view across all sales and marketing channels to drive predictability and improve revenue. But this is challenging because salespeople and marketers generally have different metrics. Further, marketers tend to speak a language that sales teams seldom understand. Common obstacles for sales and marketing collaboration include different languages between sales and marketing, and the lack of credibility among salespeople for someone without sales experience. Marketing can improve the transparency of the sales process by tracking customer progress through different stages of the sales funnel. This increased transparency can form the basis for collaboration between marketing and sales. But it is important for marketing to map customer insights to the sales funnel and explain how the insights can improve the sales process.

Analytics Processes

How does a business combine data and heuristics?

Marketing decisions should depend on the information gathered, but it is never possible to gather all the information. It is, therefore, important to blend analytics with heuristics to create a better marketing-mix model by integrating nonmix lessons learned over time. For example, consider a situation wherein the goal is to use analytics across marketing elements to maximize the return. The reality, though, is that according to analytics, short-term trade ROI is going to be higher than short-term advertising ROI. This is because trade marketing has an immediate effect on sales, whereas advertising normally has a smaller short-term effect. The total value from advertising is realized over time, whereas most of the value for advertising is realized within the short term.

Although it is easier to lift sales with short-term levers such as price discounts rather than with long-term levers such as new customer acquisition, it is not the best decision to reallocate all advertising money to trade. So a business would need to consider including metrics beyond sales, such as brand and advertisement awareness or word of mouth, to evaluate the value of marketing-mix elements.

The biggest challenge to accomplishing this is incorporating heuristics into the analytics process in the long run. The solution is to learn over time. By following a measurement cycle—"plan, execute, measure, evaluate, learn"[3]—companies can apply knowledge learned from previous projects to compare and contrast insights into new projects.

Does the language of marketing analytics match the language of the business?

Consultants typically view the messaging of the results as the key reason for lack of implementation of the findings. Three factors help develop a persuasive story using marketing analytics. The first step to telling a good story is to clearly define, explain, and widely share the primary metric for evaluating resource allocation. By increasing transparency and clarity, analytics teams can improve their influence on the process. Second, analytics managers need to ensure that the model is in sync with brand strategy and other data to which executives are exposed. This helps the message of the model fit the larger story. Finally, simple and readable models have a much stronger impact on decision making. Data visualization and simulation software help open the black box and help managers play with the marketing analytics system to understand its process and benefits.

Organizational Change

How does a business develop effective feedback loops?

Feedback loops can be developed by setting performance or ROMI thresholds, making recurring improvements, and celebrating accomplishments of both the marketing analytics and brand teams.

[3] Paul Flugel and Dafna Gabel, "Marketing Mix Analysis: Heuristics to Empower Action," conference presentation, Marketing Science Institute, http://www.msi.org/conferences/presentations/marketing-mix-analysis-heuristics-to-empower-action/ (accessed Apr. 23, 2014).

It is useful to start with an idea of the end goal of the analytics-driven organizational change in mind. This determines the expected long-term payoff and allows management to establish key criteria for accepting initiatives proposed by analytics. Communicating the end goal and the criteria early in the journey improves the relevance of analytics activities.

An organizational change journey must be mapped to reach the end goal. The journey begins with customer insight. Focusing on only profit will lead to little relevance for the brand and to increased issues with customer churn and dissatisfaction. It is, therefore, important to focus analytics on understanding actual shopping behavior, rather than the sophistication of the models. The key is to drive customer behavior by understanding customers' attitudes and the determinants of their attitudes. Customer transactions and profits would result from developing a system that delivers on customer needs.

The journey, therefore, begins with understanding the customer data available within an organization and developing systems for capturing data that is unavailable but necessary. Analytics then drives customer insights, which can be combined with management heuristics to develop customer management decisions. The success of this process depends on managers' willingness to separate fact from fiction and look to data to test their business and customer hypotheses. During this process, it is important to keep a focus on customer feedback as the basis for evaluating the strategy. A customer-focused incentive structure would also enable long-term management focus on continuous customer feedback–based improvement.

Looking Ahead

More than 40 years later, John D. C. Little's observations are still relevant:

> People tend to reject what they do not understand. The manager carries responsibilities for outcomes. We should not be surprised if he prefers a simple analysis that he can grasp, even though it may have a qualitative structure, broad assumptions, and only a little relevant data, to a complex model whose assumptions may be partially hidden or couched in jargon and whose parameters could be the result of obscure statistical manipulation.[4]

Firms have the ability to do extensive analysis and develop sophisticated marketing analytics tools. But there is still a gap between analytics and action, communication and buy-in, and testing and learning. It is likely that firms and their analytics functions need more marketing and less science. Organizations have learned how to measure customer value and infer insights from customer data, but connecting these insights to the decision maker is still a missing piece.

[4] John D. C. Little, "Models and Managers: The Concept of a Decision Calculus," *Management Science* 50, no. 12, supplement (2004): 1,841–53.