Benchmarking Pricing Decisions

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ABSTRACT

Academics and practitioners agree that better pricing strategies are important drivers of return on investment, yet this premise has not been fully tested. We develop a new pricing adherence fraction (PAF), and then investigate if it is related to changes in return on investment (ROI) for a firm's products. We test this PAF–ROI performance relationship using ten pricing strategies defined and quantified by Noble and Gruca (1999) using logit modeling and regression analyses. Survey results of 385 durable capital goods manufacturers in business-to-business (B2B) markets provide the data for this research. A statistically significant PAF-ROI relationship was found between using the best pricing strategy for a given pricing situation and increased return on investment. Confidence interval analysis reveals that pricing mistakes can cost firms up to a 9.46% decrease in ROI. The PAF methods and procedures for a particular pricing situation allow a current pricing strategy to be systematically compared to the best pricing strategy out of ten possible pricing strategies.

DSJ Topics: Pricing, Decision Support Systems, Benchmarking, Performance Metrics and Evaluation, Revenue Management

DSJ Methodologies: Regression Methods, Survey Research

INTRODUCTION

Organizations, and their sales agents and executives, have many choices regarding how to price their products. Traditional pricing studies focus on what pricing strategy is used in a given industry and how frequently. Price is one of the most effective variables that managers can use to influence demand, as documented by the field of economics. Pricing is not only important for a product's return-on-investment point of view, but also from an operational (ABC, 2013) and marketing (Kotler, 2013) perspective. Fleischmann, et al. (2004) call for both the operations and marketing areas to work jointly to look at key pricing strategies, and how they are going to impact the company's profitability. The academic community has identified internal and external drivers for various pricing strategies (Noble and Gruca, 1999), perhaps driven by the success of revenue management research (Bitran and Caldentey 2003).

Revenue management is a dynamic pricing, overbooking, and allocation of perishable assets across market segments in an effort to maximize short-term revenues for the firm. Airlines, rental cars, cruise ships, hotels, theaters, and sports stadiums are a few of the situations where revenue management methods have been used to maximize revenue. For example, XYZ (1999) test five-hotel room booking heuristics under 36 realistic hotel operating environments. A subsequent article by VXY (2003) compared the performance of a new Price Setting Method (PSM) for hotels to the industry standard Bid Price Method (BPM). The PSM produces an average revenue increase of 34 percent, which can be thought of as the upper bound on realistic revenue increases.

Although these two articles developed the methods explicitly for hotels, they could be easily adapted to these other perishable asset environments. In these two articles, algorithms for pricing were for short time horizons; prices were often reset daily if not more frequently. The planning horizon was usually less than a year. In these revenue management situations, the cost structure is fixed, and there is not enough real time data to react to competitor behavior. So these tools utilize market segment time series forecast and existing market segmentations to set prices. In ABC (2005), a short-term pricing tool called the Economic Payout Model for Service Guarantees (EPMSG) was developed. Here, a short-term price was set as the payback to customers for a service upset.

In this paper, our focus shifts from setting short-term prices (payouts) before (after) the sale to developing a tool for assessing the quality of a firm's long-term pricing strategy. Therefore, the range of information that we evaluate is much broader, and includes the competitive (external) environment as well as the firm's internal characteristics.

We address the following research question, "Does adherence to normative pricing strategies increase return on investment for a firm's products?" To answer this question, we developed a new "price adherence metric" that measures the "current pricing strategy used by the firm for a specific product" relative to a "best pricing strategy among a set of ten pricing strategies." The pricing situation, based on Noble and Gruca (1999) research, is defined by a set of internal conditions (i.e., also called determinants) such as costs and capacity utilization, and external conditions such as market elasticity and product differentiation. An on-line survey was designed and administered to differentiated, durable capital goods manufacturers in business-to-business (B2B) markets. A total of 385 complete and valid surveys were analyzed to evaluate this research question. Our data was analyzed using logit modeling and regression analysis.

Noble and Gruca (1999) define ten pricing strategies in a two tier framework that is shown in Table 1. The first tier is defined by the following four pricing situations—new product pricing, competitive pricing, product line pricing, and cost-based pricing. Within each of these four pricing situations they define ten unique pricing strategies (i.e., the second tier). Each of the ten pricing strategies in Table 1 is discussed later in this article. Noble and Gruca's (1999) logit model estimation results for all of their determinants are summarized in Tables 2 and 3. The determinants define the pricing situation using internal and external criteria that determine the managers' choices regarding a pricing strategy.

Logit models are used to benchmark the pricing strategy used by the executives that responded to our survey.

Tables 1, 2 and 3 About Here

This article is organized in the following order. A literature review is presented next to define the PAF and provide the background logic for this research. An example price adherence fraction (PAF) computation using logit models is also provided. Then the research hypothesis and design are presented, followed by a section that describes the survey and sample data. Next, the results of the data analyses are presented. The paper concludes by summarizing the results, limitations, and future research directions.

LITERATURE REVIEW

The research premise is that "adherence to normative pricing strategies increases return on investment." We use three key constructs to test this premise – normative pricing strategies, the pricing adherence fraction, and return on investment. We now focus on establishing the content validity of each construct. Later, we will formally define the null hypothesis and related metrics.

Normative pricing strategies

Ten normative pricing strategies are defined in Table 1 from the Noble and Gruca article (1999, p. 438), and used here. Normative means creating or conforming to a standard or expert consensus about a particular concept or practice in a field of study. Noble and Gruca group these pricing strategies into four pricing situations—new product pricing, competitive pricing, product line pricing, and cost-based pricing. A pricing situation is a set of key product, economic, market, and information conditions (i.e., Noble and Gruca call them determinants) that make a given pricing strategy superior in theory to any other strategies. That is, the pricing strategy must best fit the operating conditions. We briefly review these ten pricing strategies, but please reference Noble and Gruca classic research (1999) for a more complete discussion and associated references.

Skim pricing, penetration pricing, and experience curve pricing are most appropriate in a new product-pricing situation (Dean 1950; Schoell and Guiltinan 1995; Telles 1986). When there is a high degree of product differentiation and demand is expected to be fairly inelastic initially, skim pricing is preferable (Jain 1993; Nagle and Holden 1995; Schoell and Guiltinan 1995). Here, the price is set very high at the beginning to maximize revenues from the "early adopters" of the new product who have a very high willingness to pay. The price is expected to drop over time as demand becomes more elastic.

Penetration pricing and experience curve pricing are very similar in that both set the new product's price very low. But the motives are different. Penetration pricing is primarily motivated by the desire to expedite new product adoption. Experience curve pricing is motivated by the desire to take advantage of a firm's competitive strength in moving quickly up the learning curve and down the unit cost curve (Jain 1993; Nagle and Holden 1995; Schoen and Guiltinan 1995; Telles 1986). That is, as volume increases, unit cost decrease.

Three competitive pricing situations are price leadership, parity pricing, and low-price supplier. A competitive pricing situation is determined by a product being in the late stages of its product life cycle (Guiltinan, Paul, and Madden 1997; Kotter 1997), and being in an environment where demand is relatively easy to forecast (Jain 1993). Price leadership is characterized primarily by having a very large market share (Jain 1993; Kotter 1997). In this environment, a firm can set the price for the market and expect the rest of the market to set lower prices since they do not have as much market clout. Parity pricing involves being a follower of the price leader and keeping a relatively constant price differential. The low-price supplier, like the parity pricer, is not in a market leadership position. But because they have a lower cost structure (Nagle and Holden 1995) and the technology to better exploit learning curve effects (Jain 1993), they can attempt to undercut the competition to gain major volume and compensate for their low prices.

Complementary product pricing, bundling pricing, and customer value pricing are most appropriate in a product line-pricing situation as shown in Table 1. This situation is characterized by a product having supplementary and/or complementary products (Guiltinan, Paul, and Madden 1997). Complementary pricing is essentially loss leader pricing—one product is sold at a very low price to attract customers, and profit is made by selling complementary products at a high markup. This works well when switching costs are high for the customers; once they are hooked with the suite of products, it would be very costly for them to change brands (Tellis 1986). Bundling pricing is appropriate in a contract selling environment where the seller packages a set of products whose total price is less than the sum of their typical individual prices (Jain 1993). Customer value pricing is essentially "stripping down" products features so that it can be offered at a lower price.

The fourth and final pricing situation is the cost-based situation where projecting demand is extremely difficult relative to all other pricing situations (Guiltinan, Paul, and Madden 1997). In this situation, the traditional cost-plus strategy is most appropriate. Here, price is set as a fixed percentage markup over unit costs.

Pricing adherence fraction

Noble and Gruca (1999) developed logit equations for each of the ten pricing strategies as a function of environmental determinants. Tables 1 to 3 summarize their two-tier pricing framework and equation parameter estimates for each determinant and associated pricing strategy. Examples of internal determinants include capacity utilization and costs, while external market deterinants include variables like market share and brand elasticity. Clearly, these determinants reflect a longer-term view of pricing than short-term revenue management research.

The Noble-Gruca logit equations give the likelihood of a firm using the theoretically best pricing strategy, given the set of internal and external environmental conditions (i.e., the pricing situation). The logit function defined as the natural log of the odds is given by Equation (1).

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \Lambda + \beta_k X_k \qquad (1)$$

Where the β's are the fitting parameters for a given strategy (see Tables 2 and 3) and the X's are the independent variables representing the set of strategy determinants for that the given strategy. The above relationship can be written as a probability defined by Equation (2).

$$p = \frac{1}{1+e^{-(\beta_0 + \beta_1 X_1 + \Lambda + \beta_k X_k)}} \qquad (2)$$

The value of p is the probability that a pricing manager (the sample frame that Noble and Gruca used) would select a given pricing strategy given the state of the environmental variables X1, X2, … (i.e., a particular pricing situation).

The pricing adherence fraction (PAF) is the ratio of two logit probabilities for a specific pricing situation as depicted in Equation 3. That is,

$$\text{PAF} = \frac{\text{Logit probability of pricing strategy used (adopted) by the firm}}{\text{Maximum logit probability of 10 Noble-Gruca pricing strategies}} \qquad (3)$$

The PAF measures how close the pricing strategy actually used by the company and selected by the survey participant is to the optimal (highest logit probability) pricing strategy determined by Noble and Gruca ten logit equations. PAF is bounded by 0 and 1. A 1 implies that the sales agent/pricing executive chose the optimal strategy, and as the PAF gets closer to 0, the quality of their pricing strategy decision gets worse. Low PAF's mean the firm's executives may not be using the best pricing strategy for their product-firm-market pricing situation.

We ask our sample of executives, for each product that they sell, to select the pricing strategy they use. Their answer becomes the numerator of our new "pricing adherence fraction" given the company's internal and external conditions. We used the Noble-Gruca logit coefficient values in Tables 2 and 3, since our survey sampling frames are essentially the same. The denominator probability is the result of inserting independent variable values into all ten of Noble and Gruca logit functions, and selecting the function that has the highest predicted probability.

Let's consider the following example. We assume that the product-survey respondent has chosen Noble and Gruca's "Customer Value Pricing" strategy as the strategy that best represents how they priced that product. For the numerator in the PAF, we use the fact that $p = \frac{1}{e^{-(\beta_0+\beta_1 X+\beta_2 X_2+...)_1}+1}$ in logit modeling, where p is the probability that the respondent would have their optimal strategy be Customer Value Pricing given the set of determinants $X_1, X_2,..,X_n$.

If our product-survey respondent combination actually used Customer Value Pricing, then their determinants for this strategy would be, Ease of Detecting Price Changes, Market Coverage, Market Growth, and Brand Elasticity as shown in Table 3. Let's say the corresponding values for our product-survey respondent for these determinants were 1, 7, 7, and 7, respectively. For Ease of Detecting Price Changes, the scale goes from 1 (Difficult) to 7 (Easy). For Market Coverage, the scale goes from 1 (All Segments) to 7 (One Segment). For Market Growth, the scale goes from 1 (Low) to 7 (High). For Brand Elasticity, the scale goes from 1 (Insensitive) to 7 (Sensitive). We use the same scales as Noble and Gruca. Then, the probability in the PAF numerator would be 1/(exp(-(-3.86)-(-.26)*1-(.24)*7-(.19)*7-(.16)*7) + 1) = 0.503, using the Noble and Gruca's logit coefficients in Table 3. For the denominator, we would plug in our product-survey respondent's determinants for each of the ten pricing strategy equations, and select the maximum probability, which is 0.76 using Skim Pricing. The optimal pricing strategy for this product-firm is Skim Pricing. Inserting the client's survey responses into the remaining nine logit pricing equations would have yielded probabilities smaller than 0.76. So, the PAF is equal to 0.503/0.760 = 0.662. The PAF of 0.66 means that for this product-firm situation their pricing strategy is 66% of the ideal pricing strategy, and therefore, the firm is not using the best pricing strategy. The PAF value is important to know, but it would be more important if we could also find a statistically significant relationship between PAF and ROI.

Return on investment

Return on investment of the product is the natural logarithm of the reported annualized ROI for that product since the current pricing strategy has been in place. Our untransformed ROI distribution is skewed, so we took the natural log (ln) of it (LOGROI) to better attain the normality assumption. For example, if the survey respondent indicated a ROI of 17.8%, the natural log (LOGROI) is -1.726. This dependent variable transformation led to normally distributed errors. The smallest coefficient error estimates possible result with normally distributed residuals (Johnston, J., DiNardo, J., 1997). Later in this article, the normality assumption is important for computing valid confidence intervals for ROI as PAF varies.

RESEARCH HYPOTHESIS AND DESIGN

The research design requires the use of Noble and Gruca (1999) two-tier pricing situation and strategy framework and their logit equations, the new PAF metric, our survey and results that mimic the Noble and Gruca survey, and evaluating the following hypothesis using logit and regression statistical analysis. The null hypothesis is formally stated as follows:

H_o: *The pricing adherence fraction (PAF) is positively associated with the natural logarithm of the reported annualized return on investment (ROI).*

The PAF methodology is to administer our survey to an appropriate sample of company executives, compute the probability given the set of internal and external conditions for each of the ten Noble and Gruca pricing strategies plus the one the firm currently uses, and then compute the respective PAFs. After statistical checks on regression assumptions like normality and constant variance, certain variable transformations may be necessary. Once the PAF-ROI data set is validated, regressions are run to see if PAF is related to LOGROI.

SURVEY AND DATA CHARACTERISTICS

The target respondents for our survey were senior-level sales agents and pricing executives including the President of the firm. These managers are in the best position to answer the survey questions because of their years of experience, expertise, and access to sales and operational performance data. Therefore, the unit of analysis is the executive. Miller and Roth (1994) and Phillips (1981) indicate that high-ranking informants tend to be more reliable sources of information because they are deeply involved in sales initiatives and results. The industry experts who reviewed the preliminary survey also provided insights as to the type of job titles that would best reflect knowledge about various pricing initiatives.

The target population is the differentiated, durable, capital goods manufacturers in B2B markets based in the United States. Participating organizations, as shown in Table 4, had an average sales volume in the range of US $21– 70 million per year and an average number of employees in the range of 100–200. We chose this frame, similar to Noble and Gruca (1999), because these industries utilize the broadest range of pricing strategies.

We applied Dillman's (2007) total design methodology to conduct the survey. Each executive was asked to select the pricing strategy most fitting for each of the top three selling (dollar value) products that her/his firm sells. We also collected extensive information on both the internal and external conditions at the time of the pricing decision.

For the initial sample frame, we obtained survey participant contact information for manufacturing firms from Dunn and Bradstreet and the Supply Chain Council (2004) organization. The initial list of firms encompassed all of the manufacturers belonging to the standard 15 SIC codes (each manufacturer is classified in only one of these codes). The objective of the sampling plan was to ensure that a large number of firms operating in different types of selling environments were included in the sample, and thereby, encompass all ten pricing strategies defined by Noble and Gruca (1999). Table 4 provides a listing of these SIC codes, the response profile, and survey questions related to this article.

Table 4 About Here

Following the survey strategy and methods advocated by Dillman (2007), a total of 1,511 senior level managers were invited to participate in an online survey. A cover letter encouraging participation in the Internet survey was mailed to the entire sample. We then followed this up with three email contacts with the potential informants including a link to the survey followed with two brief reminder letters. A response was received from 108 individuals indicating that they were not in a position to complete the questionnaire. Common excuses include change of jobs, retirement or only peripheral involvement with pricing strategies. Of the remaining 1,403, a complete questionnaire was returned by 385 respondents indicating a response rate of 27.4%. This response rate is in excess of 10% that is common for survey-based research in the literature (Koufteros et al., 1998).

We next assessed all data for non-normality. This data analysis did not provide any evidence to cause concerns (except for ROI that is previously explained and tested). A final set of tests evaluated the potential of non-response bias. As indicated by Armstrong and Overton (1977), we test for evidence of non-response bias by comparing responses between early and late submitted questionnaires through independent sample t-tests. We also compared the response sample to the total pool of invited participants along the dimensions of primary industry classification and firm size. These statistical tests revealed no non-response bias.

STATISTICAL RESULTS AND FINDINGS

A general regression equation using Minitab 16 (2010) is shown in Table 5 that is statistically significant at $\alpha < 0.01$ and $n = 385$. Therefore, selecting the correct pricing strategy for a certain product-firm situation directly impacts product profitability and return-on-investment. Moreover, the PAF coefficient is positive as hypothesized. That is, as PAF increases so does LOGROI. Also, the correlation between PAF and LOGROI is 0.139.

Table 5 About Here

A possible problem with the regression in Table 5 is significant heteroscedasticity. Heteroscedasticity is a characteristic of a data set where some sub-populations may have different variances. The presence of heteroscedasticity casts doubt on the validity of confidence intervals. Park's test (1966) was run, and heteroscedasticity was proven. Therefore, we regressed the inverse of LOGROI against PAF in a standard attempt to eliminate heteroscedasticity. This result is shown in Table 6. The

PAF coefficient is statistically significant at $\alpha = 0.012$. Residual and normal probability plots for this regression were linear enough, so that the assumption for valid confidence intervals holds (i.e., only gross departures from linearity are a cause for concern). Note from Table 6 that the coefficient on PAF is negative; this is proper since we are trying to predict the inverse of LOGROI. Moreover, the p-value on this coefficient is below the standard .05 threshold, indicating that PAF does positively impact LOGROI.

To further test for heteroscedasticity in regression we use Park's test (1966) as show in Table 7. Park's test shows no statistical significance (i.e., $\alpha = 0.193$) in the relationship between ln(residuals**2) and ln(PAF). Therefore, there is no statistical evidence of heteroscedasticity in our inverse LOGROI regression, and therefore, our inverse LOGROI regression has valid confidence intervals.

Table 8 shows how ROI varies as PAF goes from its lower limit of 0 to its upper limit of 1. As shown in the table, one-tenth increments in PAF translates into about one-half percent changes in ROI. For our specific product-firm-market data set (i.e., n = 385), ROI varies from 14.3% to 19.2% depending on how bad (PAF = 0.0) or good (PAF = 1.0) the firm's pricing strategy is for their situation.

What is one-half a percent (or more) increase in ROI worth for your business? For example, a firm with sales of $10 million that increases its PAF one-tenth results in extra revenue of $50,000. For $100 million in sales, the PAF model predicts extra revenue of $500,000 with a one-tenth increase in the PAF. With $1 billion in sales and similar assumptions we generate an extra $5 million. And, of course, if we can increase our unique PAF more than one-tenth the economic benefits are greater, in some case, much greater.

A 95% confidence interval analysis when PAF = 0 and 1 in Table 8 provides additional evidence of the importance of a firm using the best pricing strategy if it wants to maximize ROI. For example, for a PAF of 1.0, our regression equation to predict 1/LOGROI is 0.866 - .086 * PAF, which results in 1/LOGROI = 0.780. LOGROI is then 1/0.780 = 1.283. And therefore ROI, using base 10 logarithms, is then $10^{(1.283)}$ = 19.176, as shown in Table 8.

A 95% confidence interval for the dependent variable, 1/LOGROI, in general is the predicted 1/LOGROI $\pm t\left(\frac{\alpha}{2}\right) * S(YX) * \sqrt{h}$, where the *t* value is 1.96, *S(YX)* the regression model standard error (0.253), and h is 1 / *n* + $(prediction - meanPAF)^2$/*SSX*. $SSX = \sum_{i=1}^{n}(X(i) - meanPAF)^2$, where *X(i)* represents the PAF for the *i*th observation in the regression database. The sample size, *n*, is 385, mean PAF is 0.72, and *SSX* is 54.59. Therefore, *h* for our example prediction at a PAF of 1.0 is 1/385 + $[1.0 - 0.72]^2$/54.59 = 0.004. Our 95% prediction interval of 1/LOGROI at a PAF of 1.0 is 0.780 ± 1.96*0.253*$\sqrt{.004}$ = (0.749, 0.811). Therefore, the 95% confidence interval for ROI when PAF = 1.0 and ROI = 19.176% in Table 8 is [$10^{(1/.749)}$, $10^{(\frac{1}{.811})}$)] = (17.08%, 21.67%). Likewise, our 95% confidence interval when PAF = 0.0 and ROI = 14.292% is (12.21%, 17.09%).

Given our sample size and the inherent variability in the prediction error, the ROI for this array of products could be anywhere between 12.21% and 21.67%, depending on how well the pricing strategy was selected. The ROI 95% overall confidence interval gap between 12.21% and 21.67% is 9.46%. This ROI performance gap is large enough to warrant significant management attention to getting the pricing strategy right for a given set of environmental conditions.

Tables 6, 7, and 8 About Here

CONCLUSIONS AND DISCUSSION OF RESULTS

Executives and researchers have long thought that their choice of a pricing strategy for a given product and market has a direct impact on product profitability and return-on-investment. But numerical proof of this performance relationship is sparse. The findings and relevant managerial implications of our research can be summarized as follows.

- The new measure defined in this article—the pricing adherence fraction (PAF)—provides the metric to normalize and benchmark the actual pricing strategy adopted by a firm with the best of ten alternative pricing strategies. The PAF is bounded by 0 and 1. A 1 implies that the sales agent/pricing executive chose the optimal strategy, and as the PAF gets closer to 0, the quality of their pricing strategy decision gets worse. The creation of this PAF metric is the first step in quantifying the performance relationship with ROI.
- Statistically significant regression analyses ($\alpha < 0.01$ or $\alpha < 0.05$ with $n = 385$) reveals that as the PAF increases toward the best (ideal) pricing strategy, reported annualized return on investment (ROI) for that product-market-firm situation also increases. Therefore, we do not reject the null hypothesis H_o.
- A major contributor to profit maximization is adherence to the best pricing strategy for the firm's unique market, product, and competitive situation (i.e., the pricing situation). For our sample frame, ROI is predicted to be 14.292% when PAF = 0 and 19.176% when PAF = 1.0. A 95% confidence interval at these extremes reveals an overall ROI confidence interval from 12.21% to 21.67% or a gap of 9.46%. Clearly, adherence to consistent and best pricing strategies for the pricing situation generates higher ROIs. Moreover, pricing mistakes can cost the firm up to a 9.46% decrease in ROI.
- We now have a "systematic PAF metric and procedure" to measure pricing adherence and its impact on ROI for any firm and industry. A firm can "benchmark" its current pricing strategies for each product-market situation to the best of ten alternative pricing strategies. Departures from ideal pricing decisions can be identified, monitored, and corrected, or at least trigger a high level executive reexamination of the firm's current

pricing strategy. The PAF methodology can be applied to a single product or product line, a sales agent or department, a division, a market segment or sales region, or an entire company.

- The evaluation of a firm's pricing strategy portfolio can be accomplished with the PAF methods defined here with the dual objectives of choosing the best pricing strategy for the situation and increasing the return on investment. There are similarities between consistent and best pricing policies, and reducing product and process variability by better quality management. Adherence to consistent pricing strategies can now be measured like the quality control methods used for product specifications. A fact-based decision support system for pricing decisions, similar to today's proven quality control support systems, is overdue.

This research study has several limitations that should be considered. First, we evaluate a buyer-seller relationship on the basis of the seller's view. It would be useful in future research to have both the buyer and seller's opinion (dyadic approach) to find whether they have a common perspective. Second, our unit of analysis was the complete sales force with the top-level executive (President and Senior Manager) as the key respondent. Additional research is required at lower levels of sales management. This simultaneous gathering and analysis of data at different organizational levels offers a promising avenue for inquiry, and may identify different pricing viewpoints and alignment issues. Third, sales agent and executive experience, relationship building skills, and behavioral aspects of selecting the best pricing strategy can be investigated in more detail. That is, what are the best practice drivers of closing a sale, and selecting the best pricing strategy to increase return-on-investment. Finally, logarithms and possibly the inverse of logarithms make the interpretation of results difficult. That is why a carefully built table of results, like Table 8 here, and confidence interval analyses are important to properly communicate to practicing managers.

Although we posited that our target market of "capital intensive, durable goods manufacturers in the U.S." would provide the most thorough test to-date of the normative pricing strategies, future research can target different goods-producing (e.g., automotive, chemical, furniture, locomotives, appliances) or service industries (e.g., banking, consulting, transportation, and communication services). It may be that a business in a service environment might not exercise the full range of the ten generic pricing strategies examined here. For example, the three pricing strategies defined in Table 3 of bundled pricing, complementary pricing, and customer value pricing offer fertile areas for service pricing research. Jet engines and iPhones and their service contracts, insurance policies, and even a cup of Starbucks coffee, provide interesting situations to test the PAF methodology. And, each industry may have a different set of generic pricing strategies.

Finally, in future research, the logic of the PAF methodology and Equations 1 to 3 may be applied to any "current practice" versus "ideal and best practice" set of metrics. For example, a stock trader, investment firm, or mutual fund might compare their current trades and performance to a set of ideal (optimal) trades and performance for a particular operating environment and time frame. And, of course, it might be enlightening to study current versus ideal/best pricing strategies in a focused area of U.S. health care using the analytical methods defined here.

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Author(s) articles (ABC, etc.) will be added later.

Table 1 Industrial Pricing Strategy Definitions (from Noble and Gruca, 1999, p. 438)

New Product Pricing Situation

1. *Price Skimming*: We set the initial price high and then systematically reduce it over time. Customers expect prices to eventually fall

2. *Penetration Pricing*: We initially set the price low to accelerate product adoption

3. *Experience Curve Pricing*: We set the price low to build volume and reduce costs through accumulated experience

Competitive Pricing Situation

4. *Leader Pricing*: We initiate a price change and expect the other firms to follow

5. *Parity Pricing*: We match the price set by the overall market or the price leader

6. *Low-Price Supplier*: We always strive to have the low price in the market

Product Line Pricing Situation

7. *Complementary Product Pricing*: We price the core product low when complementary items such as accessories, supplies, spares, services, etc., can be priced with a high premium

8. *Price Bundling*: We offer this product as part of a bundle of several products, usually at a total price that gives out customers an attractive savings over the sum of individual prices

9. *Customer Value Pricing*: We price one version of our product at very competitive levels, offering fewer features than are available on other versions

Cost-based Pricing Situation

10. *Cost-Plus Pricing*: We establish the prices of the product at a point that gives us a specified percentage profit margin over our costs

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Table 2 Logit Model Estimations and Determinants for All Pricing Situations and Strategies (from Noble and Gruca, 1999, pp. 448-450)

	Determinants (Expected Sign)	Coefficient Estimate
New Product Pricing Situation	Product Age (-)	-0.25
Skim Pricing	Product Differentiation (+)	0.31
	Major Product Change (+)	-0.33
	Costs (+)	0.08
	Cost disadvantage: Scale (+)	0.71
	Cost disadvantage: Learning (+)	-1.10
	Market Elasticity (-)	-0.00
	Brand Elasticity (-)	-0.14
	Capacity Utilization (+)	0.05
Penetration Pricing	Product Differentiation (-)	0.12
	Major Product Change (-)	-0.28
	Costs (-)	-0.20
	Cost advantage: Scale (+)	1.14
	Market Elasticity (+)	0.48
	Brand Elasticity (+)	-0.43
	Capacity Utilization (+)	0.07
Experience Curve Pricing	Product Differentiation (-)	0.21
	Major Product Change (-)	-1.05
	Costs (-)	-0.00
	Cost advantage: Learning (+)	0.12
	Market Elasticity (+)	0.06
	Brand Elasticity (+)	0.16
	Capacity Utilization (+)	-0.20
Model Intercept		-2.25
Competitive Pricing Situation	Product Life Cycle (+)	0.40
	Ease of Estimating Demand (-)	-0.01
Leader Pricing	Market Share (+)	0.04
	Costs (-)	0.11
	Cost advantage: Scale (+)	0.61
	Cost advantage: Learning (+)	0.56
	Ease of Detecting Price Changes (+)	0.07
	Market Elasticity (-)	0.10
	Capacity Utilization (+)	-0.22
Parity Pricing	Market Share (-)	-0.22
	Costs (-)	0.48
	Cost disadvantage: Scale (+)	0.08
	Cost disadvantage: Learning (+)	0.41
	Ease of Detecting Price Changes (+)	-0.32
	Market Elasticity (-)	0.17
	Capacity Utilization (+)	0.05
	Product Differentiation (-)	0.23
	Brand Elasticity (+)	0.34

Table 3 Logit Model Estimations and Determinants for All Pricing Situations and Strategies (from Noble and Gruca, 1999, pp. 448-450)

Competitive Pricing Situation	**Determinants (Expected Sign)**	**Coefficient Estimate**
Low-Price Supplier	Market Share (-)	-0.04
	Costs (-)	-0.65
	Cost advantage: Scale (+)	0.96
	Cost advantage: Learning (+)	-0.36
	Ease of Detecting Price Changes (-)	0.18
	Market Elasticity (+)	0.01
	Capacity Utilization (-)	-0.25
	Product Differentiation (-)	0.117
	Brand Elasticity (+)	0.28
Model Intercept		-3.86
Product Line Pricing Situation	Sell substitute and/or complimentary products (+)	0.77
Bundling Pricing	Per Sale/Contract Pricing (+)	1.01
	Brand Elasticity (+)	0.24
Complementary Product Pricing	Profitability of accompanying sales (+)	-0.13
	Profitability of supplementary sales (+)	0.34
	Switching Costs (+)	0.00
Customer Value Pricing	Ease of detecting price changes (-)	-0.26
	Market coverage (+)	0.24
	Market Growth (-)	0.19
	Brand Elasticity (+)	0.16
Model Intercept		-3.86
Cost-Based Pricing Situation	Ease of estimating demand (+)	0.13
Model Intercept		-0.20

Table 4 Survey response data profile and questions

Title of respondent	Percent	Organization annual revenue	Percent
President	94%	$1-$20 million	41%
Senior Manager-Sales	6	$21-$70 million	33
		$71-$242 million	13
		$243-$710 million	6
		over $710 million	7

Number of employees	Percent
Less than 200	65%
201-500	18
501-1,000	6
1,001-1,500	3
greater than1,501	8

4 digit SIC codes	Industry	4 digit SIC codes	Industry
3523	Farm	3571	Electronic computers
3531	Construction	3663	Radio and TV communication equipment
3532	Mining	3711	Tractor and tractor trucks
3537	Industrial trucks and tractors	3721	Aircraft
3541	Machine tools: Cutting	3743	Railroad equipment
3542	Machine tools: Farming	3812	Search and navigation equipment
3549	Metal working machines	3823	Process control equipment
3554	Paper industry machines		

Survey questions

All of the variables documented in Tables 2 and 3, and used in the Noble and Gruca (1999) article were measured in our survey on identical scales. In addition, the following questions were asked.

- For your product-firm pricing situation, the top selling product over the last three years (in terms of dollar sales) is _________________?
- For your product-firm pricing situation, the SIC code is _________________?
- For your product-firm pricing situation, you use which one of the following ten pricing strategies?_________________
- For this product, the return on investment over the last three years (or however long the product has been in existence, if less) is ___________?

Table 5 Regressing the pricing adherence fraction (PAF) against the natural logarithm of return-on-investment (LOGROI)

Regression Equation

LOGROI = 1.2282 + 0.122344*PAF

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	1.22820	0.0363420	33.7957	0.000
PAF	0.122344	0.0445423	2.7467	0.006

Summary of Model
S = 0.329173 R-Sq = 1.93% R-Sq(adj) = 1.68%
PRESS = 41.8785 R-Sq(pred) = 1.04%

Analysis of Variance

Source	*DF*	*Seq SS*	*Adj SS*	*Adj MS*	*F*	*P*
Regression	1	0.8175	0.8175	0.817468	7.54435	0.006304
Error	383	41.5000	41.5000	0.108355		
Lack-of-Fit	26	13.9822	13.9822	0.537777	6.97681	0.000000
Pure Error	357	27.5178	27.5178	0.077081		
Total	384	42.3174				

Table 6: Regression of inverse of LOGROI against PAF:

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.128
R Square	0.016
Adjusted R Square	0.014
Standard Error	0.253
Observations	385

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.405	0.405	6.338	0.012228
Residual	383	24.47	0.064		
Total	384	24.88			

Source	*Coefficients*	*Std Error*	*T Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.866	0.028	31.02	0.000	0.810851	0.92061
PAF	-0.086	0.034	-2.52	0.012	-0.15339	0.01886

Table 7: Park's heteroscedascity test on the inverse of LOGROI against PAF model:

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.066
R Square	0.004
Adjusted R Square	0.002
Standard Error	2.908
Observations	385

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	14.36	14.36	1.698866	0.193219
Residual	383	3238	8.454		
Total	384	3252			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-4.96	0.174	-28.5	7.7E-97	-5.30496	-4.62112
lnPAF	-0.18	0.135	-1.3	0.193219	-0.44204	0.089606

Table 8: PAF and ROI model predictions when 1/LOGROI regressed against PAF

PAF	1/LOGROI	LOGROI	ROI Percent (base 10)
0.0	0.866	1.155	14.292%
0.1	0.857	1.167	14.679%
0.2	0.848	1.179	15.085%
0.3	0.840	1.191	15.511%
0.4	0.831	1.203	15.958%
0.5	0.823	1.216	16.427%
0.6	0.814	1.228	16.921%
0.7	0.805	1.242	17.440%
0.8	0.797	1.255	17.988%
0.9	0.788	1.269	18.565%
1.0	0.780	1.287	19.176%