A new pricing strategy evaluation model

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Abstract: Academics and practitioners agree that better pricing strategies are important drivers of return on investment (ROI), yet this premise has not been fully tested. We develop a new pricing adherence fraction (PAF) and then investigate whether it is related to changes in return on investment 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 modelling 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 is found between using the best pricing strategy for a given pricing situation and an increased return on an investment. Confidence interval analysis reveals that pricing mistakes can cost firms up to a 10% decrease in ROI. The PAF methods and procedures for a particular pricing situation allow a current pricing strategy to be compared systematically to the best pricing strategy among ten possible pricing strategies.

Keywords: pricing; decision support systems; benchmarking; survey research; regression methods; performance metrics.

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1 Introduction

Organisations, their sales agents, and their executives have many choices in pricing their products. Traditional pricing studies focus on which pricing strategy is used in a given industry and how frequently. As documented in the field of economics, price is one of the most effective variables managers can use to influence demand. Pricing is important not only for a product's return on investment, but also from operational (Collier and Evans, 2013) and marketing (Kotler, 2013) perspectives. Fleischmann et al. (2004) call for both the operations and marketing areas to work jointly in developing key pricing strategies and the ways in which those decisions impact company profitability.

Noble and Gruca (1999) defined ten pricing strategies in a two-tiered framework with internal and external drivers of these pricing strategies. We use their framework to evaluate the relationship between pricing strategy and return on investment. Research is limited on this performance relationship, while non-tested 'practical advice' on pricing abounds.

For example, Anderson et al. (2010) developed a comprehensive pricing guide for practitioners that has not been quantitatively evaluated. They posited that prices should be set based on what a customer expects the price to be. To determine the best price, customers do a perceptual value calculation and benchmark this price against other competitors' prices at higher and lower quality levels. Using a non-scientific survey of executives and company data, Hinterhuber and Liozu (2014) found 20 different ways that pricing can be innovative and effective. Ingenbleek and van der Lans (2013) determined that disconnects exist between what the normative pricing literature says is the best pricing policy and what a firm actually does.

In this research, we explore this disconnect by trying to quantify the financial impact of the degree of divergence between normative pricing theory choices and actual pricing practice. We use a normative theory approach defined by the Noble and Gruca (1999) framework that is:

a well-grounded in fundamental pricing theory

b empirically tested.

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 or determinants such as costs and capacity utilisation 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 analysed to evaluate this research question. Our data was analysed using logit modelling and regression analysis.

Table 1 Industrial pricing strategy definitions

	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 our 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.

Source: Noble and Gruca (1999, p.438)

Table 2 Logit model estimations and determinants for all pricing situations and strategies

	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 utilisation (+)	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 utilisation (+)	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 utilisation (+)	–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 utilisation (+)	–0.22

Source: Noble and Gruca (1999, pp.448–450)

Table 2 Logit model estimations and determinants for all pricing situations and strategies (continued)

	Determinants (expected sign)	*Coefficient estimate*
Competitive pricing situation		
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 utilisation (+)	0.05
	Product differentiation (–)	0.23
	Brand elasticity (+)	0.34
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 utilisation (–)	–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

Source: Noble and Gruca (1999, pp.448–450)

Noble and Gruca (1999) define ten pricing strategies in a two-tiered framework 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. The Noble and Gruca (1999) logit model estimation results for all of their determinants are summarised in Table 2. 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.

This article is organised in the following order. A literature review is first presented to define the price adherence fraction (PAF) and provide the background logic for this research. An example 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 summarising the results, limitations, and future research directions.

2 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. First, we focus on establishing the content validity of each construct. Later we formally define the null hypothesis and related metrics.

Ten normative pricing strategies are defined in Table 1 from the Noble and Gruca (1999, p. 438) and are 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 (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; 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; Tellis, 1986). Skim pricing is preferable when there is a high degree of product differentiation and demand is expected to be fairly inelastic initially (Jain, 1993; Nagle and Holden, 1995; Schoell and Guiltinan, 1995). Here, the initial price is set very high to maximise revenues from '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 both set a new product's price very low, but the motives are different. Penetration pricing is motivated primarily 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; Tellis, 1986). That is, as volume increases, unit cost decreases.

Three competitive pricing situations are price leadership, parity pricing, and low-price supplier. A competitive pricing situation is determined by a product's being in the late stages of its product life cycle (Guiltinan et al., 1997) and in an environment where demand is relatively easy to forecast (Jain, 1993). Price leadership is characterised primarily by having a very large market share (Jain, 1993). In this environment, a firm can establish the price for the market and expect the rest of the market to set lower prices because they do not have as much market power (clout).

Parity pricing involves being a follower of the price leader and keeping a relatively constant price differential. Lowe and Alpert (2010), for example, describe the evolution of reference-based prices. A reference price is the baseline price that all competitors use as a gauge to see whether their prices are reasonable. Lowe and Alpert show that for truly innovative products, a reference price stays in place much longer and is driven solely by the initial innovator. This theory fits within our leader pricing (i.e., innovator) and parity pricing (i.e., follower) strategies (see Table 1 competitive pricing situation).

A low-price supplier, like a parity price, is not in a market leadership position. However, because it has a lower cost structure (Nagle and Holden, 1995) and the technology to better exploit learning curve effects (Jain, 1993), it can attempt to undercut the competition to gain more volume and compensate for its lower 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 characterised by a product with supplementary and/or complementary products (Guiltinan et al., 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. Here, 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' a product's features so that it can be offered at a lower price.

Ingenbleek et al. (2013) evaluated a value-based pricing approach, developed metrics for how well the pricing strategy is adhered to, and then showed how their degree of adherence is empirically linked to:

a the ability to increase prices

b increased market share

c increased sales.

Our dependent variable, return on investment, was not evaluated by Ingenbleck et al. (2013).

The fourth and final pricing situation is the cost-based situation where projecting demand is extremely difficult relative to all other pricing situations (Guiltinan et al., 1997). In this situation, the traditional cost-plus strategy is most appropriate. Here, price is set as a fixed percentage markup over unit costs. Thomas et al. (2010) also note that buyers in a B2B situation are willing to pay more in negotiations if the prices in the negotiation are exact (e.g., $9,512.12) versus rounded (e.g., $9,600). Alexander et al. (2014) show prices tend to be inflated and the markup is higher when either:

a competition is less intense and/or

b a pricing unit has a strong technological orientation.

3 Price 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 2 summarise their two-tier pricing framework and equation parameter estimates for each determinant and associated pricing strategy. Examples of internal determinants include capacity utilisation and costs, while external market determinants 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's 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).

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_K \tag{1}$$

The βs are the fitting parameters for a given strategy (see Table 2) and the Xs 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).

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

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 X_1, X_2, … X_n (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,

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

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's ten logit equations. The logit probability of pricing strategy used (adopted) by the firm is obtained by:

a selecting the 'pricing situation' from Table 2 that the respondent selected for that product

b inserting the 'determinants' data into the logit equation corresponding to the 'pricing situation' and therefore obtaining the logit probability.

This logit probability represents how good, in terms of normative pricing strategy, the selected strategy is. The denominator of the PAF is then the best logit probability that could have been obtained if the absolute best 'pricing situation' had been used given the 'determinants' data.

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 the pricing strategy decision gets worse. Low PAFs mean the firm's executive may not be using the best pricing strategy for the product-firm-market pricing situation.

We ask our executives, for each product that they sell, to select the pricing strategy they use. Our unit of analysis is a specific product within an organisation. Their answer becomes the numerator of our new 'pricing adherence fraction' given the company's internal and external conditions. We use the Noble-Gruca logit coefficient values in Table 2, 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's logit functions and selecting the function that has the highest predicted probability.

Let us consider the following example. We assume the product-survey respondent has chosen Noble and Gruca's 'customer value pricing' strategy as the strategy that best represents how the firm prices that product. For the numerator in the PAF, we use the fact that in logit modelling,

$$p = \frac{1}{e^{-(\beta_0 + \beta_1 X + \beta_2 X_2 + \ldots)_1} + 1}$$

where p is the probability that the respondent would have his or her 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 the determinants for this strategy would be ease of detecting price changes, market coverage, market growth, and brand elasticity, as shown in Table 2. Assume 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 do 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 logit coefficients in Table 2. 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 this product-firm's 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.

4 Return on investment

Return on investment for the product is the natural logarithm of the reported annualised 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. Later in this article, the normality assumption is important for computing valid confidence intervals for ROI as PAF varies.

5 Research hypothesis and design

Due to disconnects between pricing theory strategic options and actual pricing practice (Ingenbleek and van der Lans, 2013), we are motivated to:

a develop a measure of the degree of disconnect (our PAF)

b see how this PAF is related to return on investment (ROI).

The research design requires the use of the Noble and Gruca (1999) two-tier pricing situation and strategy framework and their logit equations, the new PAF metric; our survey and results mimic the Noble and Gruca survey and evaluate 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 annualised 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, such as normality and constant variance, certain variable transformations may be necessary. Once the PAF-ROI dataset is validated, regressions are run to see if PAF is related to LOGROI.

6 Survey and data characteristics

The target respondents for our survey are senior-level sales agents and pricing executives including the president of the firm. These managers are in the best positions to answer the survey questions because of their years of experience, expertise, and access to sales and operational performance data. We are interested in their pricing practices and business environments for their top three selling products. 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 survey protocol was to first have the executive respondents fill out a brief questionnaire prior to filling out our complete survey. This initial questionnaire ascertained how well the executives understood their sales force and product pricing capabilities and behaviours. The executives could not see our complete survey until after they had passed this screen. This initial survey screen is important since we then had a better idea of who had price setting capabilities for their top three selling products. If the survey respondent did not have these capabilities, then the survey was ended, and we did not use the survey.

Given that we used only one survey respondent, we ensured that 'common method bias' would not occur, due to several remedies suggested by Chiang et al. (2010). First, our logic for determining the PAF is difficult for the survey respondent to guess (i.e., it is not linear, and is rather complicated). When answering the survey questions about their business environment for the product in question, and then their pricing strategies; the intent of our theorised relationship between their business conditions and optimal pricing strategy is not revealed. Second, the questions pertinent to the calculation of the PAF were dispersed widely throughout the survey to insure that responses could not be biased. Third, the final theorised relation between PAF and LOGROI, with the attendant control variables, could not have been discerned by the respondent due to the spacing of questions and the complexity of the PAF calculation.

The target population is the differentiated, durable, capital goods manufacturers in B2B markets based in the USA. Participating organisations, shown in Table 3, 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 that of Noble and Gruca (1999), because these industries utilise 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 Dun and Bradstreet and the Supply Chain Council (2004) organisation. 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 3 provides a listing of these SIC codes, the response profile, and survey questions related to this article.

Table 3 Survey response data profile and questions

	Percent
Title of respondent	
President	94
Senior manager – sales	6
Number of employees	
Less than 200	65
201–500	18
501–1,000	6
1,001–1,500	3
Greater than 1,501	8
Organisation annual revenue	
$1–$20 million	41
$21–$70 million	33
$71–$242 million	13
$243–$710 million	6
Over $710 million	7

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	Tractors 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 Table 2, 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 _________________.

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 up with three email contacts to potential informants including a link to the survey followed by 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 included 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 the 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 tested for evidence of non-response bias by comparing responses between early and late submitted questionnaires through independent sample t-tests. We ran these non-normality tests on all of the variables implied in Tables 2 and 6, and the reported ROI and PAF. All of the 95% confidence intervals on these tests covered zero, indicating no difference between early and late submissions (our early submissions came in within the first eight days of the response window; then there was a break of six days before the remainder came in). 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.

7 Statistical results and findings

A general regression equation is shown in Table 4 that is statistically significant at $\alpha = 0.01$ and n = 385. This equation uses GROWTH MARKET and SHARE MARKET as control variables in an equation that relates PAF and LOGROI. For the different combinations of control variables shown in Table 5, when regressing LOGROI against the controls and PAF, the equation in Table 4 had the highest R-square with all coefficient signs correct and statistically significant. That is, as PAF increases, so does LOGROI. Therefore, selecting the correct pricing strategy for a certain product-firm situation directly impacts product profitability and return-on-investment.

A possible problem with the regression in Table 4 is significant heteroscedasticity.

Heteroscedasticity is a characteristic of a dataset where some sub-populations may have different variances. The presence of heteroscedasticity casts doubt on the validity of confidence intervals. Table 6 summarises the results of Park's test for heteroscedasticity (1966) that regresses ln(residuals**2) against ln(PAF), ln(GROWTHMARKET) and ln(SHAREMARKET). Since all coefficients are either clearly non-significant, with one only borderline significant (p-value = .04), we cannot reject the null hypothesis of homoscedasticity. Residual and normal probability plots for this regression (not shown to save space) are linear enough that the assumption for valid confidence intervals holds (i.e., only gross departures from linearity are a cause for concern).

Table 4 Regression of LOGROI against PAF, GROWTH MARKET and SHARE MARKET

Regression statistics				
Multiple R	0.28072692			
R square	0.078807604			
Adjusted R square	0.07155412			
Standard error	0.319816547			
Observations	385			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	3	3.333838938	1.111279646	10.86479407
Residual	381	38.96967971	0.102282624	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	0.883041917	0.08018921	11.0119793	1.13502E-24
PAF	0.117564842	0.044242447	2.65728617	0.008208678
GROWTH MARKET	0.033400593	0.010249509	3.258750535	0.001219577
SHARE MARKET	0.043401168	0.011766015	3.688688896	0.0002582

Table 5 Control variable definitions

Variable	*Scale*	*Question*
GROWTH MARKET	1 (low) – 7 (high)	What is your estimate of the market growth of this product over the last six months?
SHARE MARKET	1 (low) – 7 (high)	How would you characterise your market share?
ACCOMPANYING PROFITABILITY	1 (low) – 7 (high)	What is the profitability of accompanying sales (i.e., other products) for this product?
DIFFERENTIATION PRODUCT	1 (low) – 7 (high)	How differentiated is your product from the competition?
SWITCHING COSTS	1 (low) – 7 (high)	What is the customer's cost for substituting suppliers for this product?

Figure 1 shows that our dependent variable, ROI, follows a normal distribution fairly closely. Thus, the precision of our regression estimates cannot be made any better through data transformation or new model specifications to improve normality. Figure 2 shows that, for one of our Table 4 baseline regression models, the functional form chosen for our PAF-LOGROI relationship is as good as it can get. There is no indication of bias at any point in this graph, and the graph shows constant error variance and normality of errors. Therefore, our fundamental relationship between PAF and LOGOI is as precise as we can get, given our sample size.

Figure 1 Normal probability plot of LOGROI (see online version for colours)

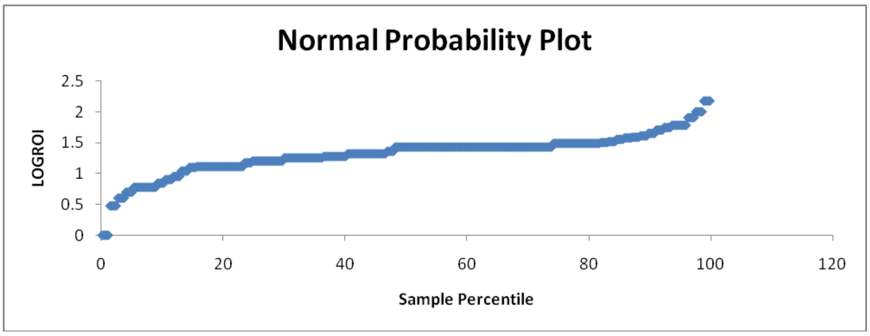

Figure 2 Residual plot for LOGROI against PAF, SHARE MARKET and GROWTH MARKET (see online version for colours)

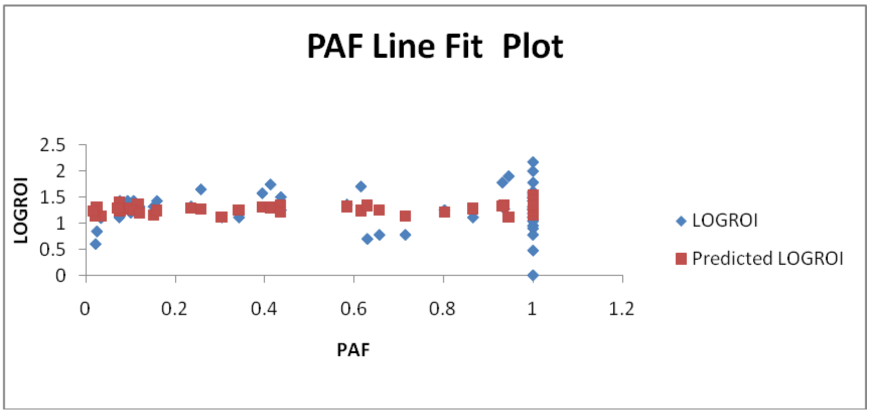

Table 7 shows how ROI varies as PAF goes from its lower limit of 0 to its upper limit of 1. In the table, a one-tenth increment in PAF translates into about one-half percent change in ROI. For our specific product-firm-market dataset (i.e., n = 385), ROI varies from 17.2% to 22.6%, depending on how bad (PAF = 0.0) or good (PAF = 1.0) the firm's pricing strategy is for its situation. Note that we made these predictions using the average values of GROWTH MARKET and SHARE MARKET of 3.8 and 5.2, respectively, from our database.

A 95% confidence interval analysis when PAF = 0 and 1 in Table 7 provides additional evidence of the importance of a firm's using the best pricing strategy if it wants to maximise ROI. For example, for a PAF of 1.0, our regression equation to predict LOGROI is 0.88 + (0.12 ∗ PAF) + (0.03 ∗ GROWTH MARKET) + (0.04 ∗ SHARE MARKET) = 1.35. And, therefore, ROI, using base 10 logarithms, is then 101.35 = 22.55% as shown in Table 8.

Table 6 Park's heteroscedascity test on the Table 4 regression model

Regression statistics				
Multiple R	0.127735671			
R square	0.016316402			
Adjusted R square	0.008570861			
Standard error	2.255751523			
Observations	385			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	3	32.15706852	10.71902284	2.106554396
Residual	381	1938.686089	5.088414931	
Total	384	1970.843157		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	–5.514274078	0.565595913	–9.749494217	3.38486E-20
PAF	0.334292229	0.312053794	1.071264749	0.284728531
GROWTH MARKET	0.075586229	0.072292525	1.045560776	0.296426749
SHARE MARKET	0.168040684	0.082988845	2.024858688	0.043578847

Table 7 PAF and ROI model predictions when LOGROI regressed against PAF, GROWTH MARKET and SHARE MARKET (based on Table 4 model)

PAF	*LOGROI*	*ROI percent (Base 10)*
0	1.235650248	17.20482453
0.1	1.247406732	17.67692552
0.2	1.259163216	18.16198097
0.3	1.2709197	18.66034635
0.4	1.282676185	19.17238691
0.5	1.294432669	19.69847787
0.6	1.306189153	20.23900479
0.7	1.317945637	20.79436378
0.8	1.329702122	21.36496184
0.9	1.341458606	21.95121714
1	1.35321509	22.5535593

For a PAF of 0 and 1, respectively, the 95% confidence intervals about the ROI prediction at the average values of GROWTH MARKET and GROWTH SHARE are (14.5%, 20.4%) and (20.4%, 24.5%). The fact that these confidence intervals do not overlap shows the importance of obtaining a better PAF. That is, having your pricing strategy fit very well with your environment (PAF = 1) guarantees better ROI performance than the case where your pricing strategy is a poor fit (PAF = 0) with your environment.

Table 8 Regression of LOGROI against PAF and GROWTH MARKET

Regression statistics				
Multiple R	0.214265278			
R square	0.045909609			
Adjusted R square	0.040914372			
Standard error	0.325050864			
Observations	385			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	2	1.942138008	0.971069004	9.190675684
Residual	382	40.36138064	0.105658064	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	1.118691704	0.049260649	22.70964204	7.13868E-73
PAF	0.097084654	0.044611058	2.176246389	0.030148943
GROWTH MARKET	0.034184515	0.010415019	3.282232513	0.001124732

Table 9 Regression of LOGROI against PAF, GROWTH MARKET, SHARE MARKET and ACCOMPANYING PROFITABILITY

Regression statistics				
Multiple R	0.287356629			
R square	0.082573832			
Adjusted R square	0.072916715			
Standard error	0.319581778			
Observations	385			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	4	3.493163661	0.873290915	8.550567184
Residual	380	38.81035499	0.102132513	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	0.851200923	0.084087951	10.12274548	1.7523E-21
PAF	0.130584987	0.045422375	2.874904449	0.0042689
GROWTH MARKET	0.027560395	0.011258889	2.447878735	0.01482161
SHARE MARKET	0.037495615	0.012672503	2.958816687	0.003281558
ACCOMPANYING PROFITABILITY	0.017610061	0.014099421	1.248991769	0.212436934

Table 10 Regression of LOGROI against PAF, GROWTH MARKET, SHARE MARKET and DIFFERENTIATION PRODUCT

	Regression statistics			
Multiple R	0.28717874			
R Square	0.082471629			
Adjusted R Square	0.072813435			
Standard Error	0.319599579			
Observations	385			
	ANOVA			
	df	*SS*	*MS*	*F*
Regression	4	3.488840085	0.872210021	8.539032664
Residual	380	38.81467856	0.102143891	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	0.855550544	0.083184341	10.28499521	4.72007E-22
PAF	0.112709536	0.04438777	2.539202476	0.011508445
GROWTH MARKET	0.030885429	0.010444077	2.957219713	0.003298213
SHARE MARKET	0.039510946	0.012174742	3.245321035	0.001277216
DIFFERENTIATION PRODUCT	0.013824076	0.011222119	1.231859727	0.218763216

Table 11 Regression of LOGROI against PAF, GROWTH MARKET, SHARE MARKET and SWITCHING COSTS

	Regression statistics			
Multiple R	0.291619753			
R square	0.08504208			
Adjusted R square	0.075410944			
Standard error	0.319151587			
Observations	385			
	ANOVA			
	df	*SS*	*MS*	*F*
Regression	4	3.59757923	0.899394808	8.829911689
Residual	380	38.70593942	0.101857735	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	0.83011624	0.08651824	9.594696303	1.15315E-19
PAF	0.108030736	0.044546253	2.425136308	0.015767905
GROWTH MARKET	0.031953487	0.010267658	3.112052108	0.001998448
SHARE MARKET	0.041071565	0.011830468	3.471677139	0.000576678
SWITCHING COSTS	0.017813358	0.011070177	1.609130378	0.108418248

Table 12 Correlations of PAF against control variables

	PAF
PAF	1.0000
GROWTH MARKET	0.1657
SHARE MARKET	–0.1238
SWITCHING COSTS	0.1338
DIFFERENTIAION PRODUCT	0.0860
ACCOMPANYING PROFITABILITY	–0.1797

Table 13 Regression of LOGROI against PAF, GROWTH_MARKET and SHARE_MARKET along with interactions

Regression statistics				
Multiple R	0.280939			
R square	0.078926			
Adjusted R square	0.066775			
Standard error	0.320639			
Observations	385			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	5	3.338866229	0.667773246	6.495273137
Residual	379	38.96465242	0.102809109	
Total	384	42.30351865		
	Coefficients	*Standard error*	*t Stat*	*P-value*
Intercept	0.883482	0.176593977	5.002899015	8.65875E-07
PAF	0.117201	0.210305087	0.557288441	0.57765934
GROWTH MARKET	0.030387	0.02140836	1.419376403	0.156611233
SHARE MARKET	0.045327	0.025175036	1.800464825	0.072582234
GROWTH * PAF	0.004926	0.027885224	0.176663948	0.859866726
SHARE * PAF	–0.00346	0.031036942	–0.111336121	0.911408751

To further prove that our PAF-LOGROI result is enduring, we augmented the regression model reported in Table 4 with a number of control variables summarised in Table 5 from Noble and Gruca (1999). Tables 8–11 summarise these control variable regression results. The idea is that if a PAF's coefficient sign and statistical significance do not change from Table 4 in these regressions, then the PAF-LOGROI relationship in Table 4 is robust. In Tables 8–11, the PAF's coefficient sign always remains positive and statistically significant. Therefore, the regression results for all control variables shown in Table 5 support the robust and statistically valid PAF-LOGROI regression model in Table 4.

Note that in Table 12, the bivariate correlations of PAF against each of the control variables show that PAF is not highly correlated (i.e., absolute value of correlations are below 0.7) with any control variable. This further supports our claim to the stability of the PAF-LOGROI relationship since this lack of correlations means that PAF cannot be a proxy for any of these controls. Also note that the regression results shown in Table 13, a regression the same as in Table 4 but with interactions added, made the predictions worse. The interaction terms are all insignificant.

8 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 summarised as follows.

- The new measure defined in this article – the pricing adherence fraction (PAF) – provides the metric to normalise 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 the 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 ($\alpha \leq 0.01$ or $\alpha \leq 0.05$ with n = 385) reveals that as the
- PAF increases toward the best (ideal) pricing strategy, reported annualised return on investment (ROI) for that product-market-firm situation also increases. Therefore, we do not reject the null hypothesis Ho.
- A major contributor to profit maximisation 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 17.2% when PAF = 0 and 22.6% when PAF = 1.0. A 95% confidence interval at these extremes reveals an overall ROI confidence interval from 14.5% to 24.5% or a gap of 10%. 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 10% 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's 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 or 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 organisational 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 behavioural 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 7, and confidence interval and control variable analyses are important to properly communicate to practicing managers.

Although we posited that our target market of 'capital intensive, durable goods manufacturers in the USA' 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, and 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 2 of bundled pricing, complementary pricing and customer value pricing offer fertile areas for service pricing research. Jet engines, iPhones and their service contracts, insurance policies, and even a cup of Starbucks coffee, provide interesting situations to test the PAF methodology. 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 its current trades and performance to a set of ideal (optimal) trades and performance for a particular operating environment and time frame. Of course, it might be enlightening to study current versus ideal/best pricing strategies in a focused area of US healthcare using the analytical methods defined here.

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