Original Article

Price optimization – How to win a strategic whole

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ABSTRACT Tradition pricing efforts without specifying time span often attempt a short-term solution. A price optimization model factored in a customer lifetime value (LTV) study recently becomes a keen interest to many businesses striving for a long-term success. This article will discuss how to advance pricing models from a tactic focus to a strategic win. As such, two modeling steps will be covered thereby: (i) an intrinsic link between profit and price is first established with a contribution of LTV, particularly in direct marketing (DM) arena; (ii) a rigorous price equation is then migrated into a tabular simulation so that practitioners can alternatively resolve an optimization in either way.

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INTRODUCTION

There are three major challenges in pricing history: (i) Pricing is a difficult process because it needs aligning diverse interests including sales-driven, cost-based, value-added and profit-oriented tactics (Nagle and Smith, 1994). (ii) Pricing involves uncertainties adherent to intuition and experience that are scarcely measurable in lack of sound framework (Simon, 1992). And (iii) Pricing turns to be cumbersome when advanced tools and in-depth analytics are required (Dolan, 1995). Suffered from these impediments, few pricing policies in today's marketplace have yet reached a desirable potential.

On the other hands, the necessity and reality of pricing optimization has been conceptually cited in vast body of literatures. According to Corey (1982) from Harvard Business School, 'All of marketing comes to focus in the pricing decision'. Yet hitherto pricing studies in progressive stages have reached the consensus that is herein outlined:

- Faulty pricing is around when intuition, instinct and experience are embedded. Historical studies on pricing power expose that any ill-conceived price, even with a slight divergence, can dramatically impact on business – disastrous or massive opportunities missed (Florissen *et al*, 2001)
- There always exists an optimal price no matter whether from theoretical standpoint or practical perspective. In any case, however, there are no simple rules but sophisticated methods are required (Dolan and Simon, 1996)
- A subjective judgment is risky with notable uncertainties whereas modeling

sophistication seems tedious to be executed in reality (Mohn, 1995)
- The gap between practice and theory has long hampered endeavors for managing the pricing dilemma in history (Nagle, 1987)
- More recent studies indicated that pricing optimization would be attainable if a sophisticated yet practical pricing model could be utilized (Feldman, 2002)

In reference to historical pricing efforts and experience, this article initiates a sound framework that warrants an optimal price while targeting a maximum profit engaged on customer LTV contributions. For a practical purpose, an alternative, cross-tab simulation is also structured for performing 'what-if' analysis, with which practitioners can readily manipulate prices when approaching its optimum in fast-paced dynamic environment. Such a conjoint analysis is attempting the empirical dilemma by reconciling modeling algorithm with actionable flexibility.

PRICING MODEL DEVELOPMENT

The new pricing model relies upon three fundamental issues to be foremost addressed: (i) establish an explicit and realistic goal to be attained with quantitative techniques; (ii) define modeling conditions and/or constraints applied within a rationed domain; (iii) develop a pricing model that interprets how price affects profit over time.

Analytic goal

The ultimate goal setting a pricing model is to achieve a maximal profit within a finite tracking horizon from initial acquisition to ongoing retention marketing. The major concerns in this context are twofold.

First, our analytic direction is targeting the maximum total net profit rather than total revenue. This should be an indubitable objective for any profit-oriented organizations to measure an utmost performance (Simon and Munack, 2000). In many situations, however, sales volume is also recognized as a decisive factor, which could be adequately weighted with tactic and/or social considerations (Urbany, 2001). No matter whether firms lie on the profit-centered policy or the revenue-balanced one, our pricing model places a measurable benchmark that guides a profit maximization or alerts an optimal trade-off between profitability and market share.

Second, literature seldom clears up the research timeframe whether it is defined for a short-term or a long-term solution, which makes a notable difference as conclusions, particular in direct marketing (DM) industry (Jain and Singh, 2002). In today's hyper-competitive global marketplace, almost no one can look upon far-reaching insights unless future stream is integrated into current marketing initiative (Hansotia and Wang, 1997). That is to say, an optimal price incurred in initial acquisition is insufficient to maintain its validity across a customer life span with your business, where a long-term contribution engaged on LTV analysis is deemed being opted to our pricing model.

Modeling conditions

As no model is virtually applied in vacuum, several assumptions must be made to facilitate modeling efficiency and validity in the real world (Kuenne, 1968; Friedman, 1984).

- Our new model is created with given data-constraining postulates specifying allowable variables while addressing profit and price but holding the others constant. As a simple rule of thumb, the fewer the variables in the set relative to the whole set of economic influences, the less ambitious the model.
- The research is conducted in a relatively static system, where the variation of interrelationships (and therefore solutions) over a given time horizon is omitted. As such, a predictive pattern based on past consumer's behaviors should statistically infer the similarities in the future.

- Optimal price is solved in the equilibrium market, in which both maximal satisfaction (to consumers) and maximal profits (to firm) are concurrently realized, subject to constraints of firm's capacity and consumers' affordability.

Pricing model

To address our analytic goal under pre-established conditions above, the linkage between a initial price and a final profit should be built within a tracking window. In most scenarios, a DM procedure is divided into up-front acquisition and follow-up retentions, where the former is referred as to short-term with subscript *s*, and latter to LTV with subscript *ltv*. Accordingly, two stages are distinctively defined but conjointly analyzed to come by a long-term solution. For the sake of concise expression, let,

CA	Cost of advertisements,
CM	Cost of merchandise (products and/or service),
P	Price of merchandise (products and/or service),
N	Number of mailings (for example, direct mail) or contacts (for example, telemarketing),
UM	Unit Margin,
RP (*or Reps*)	Number of response (that is, orders or invoices),
BE	Number of minimal response to achieve break-even,

Notice cost typically consists of *CA* and *CM*, where each should be broken down into *s* and *ltv*. In turn, an overall *Profit* can be constituted as:

$$Profit = (Profit)_s + (Profit)_{ltv} \ldots \qquad (1)$$

Since *Profit* is defined as: $(RP - BE)^{\star}UM$, meaning, any net sales exceeding breakeven generates the net profit, thus,

$$Profit = (RP_s - BE_s)^{\star}UM_s + (RP_{ltv} - BE_{ltv})^{\star}UM_{ltv} \ldots \qquad (2)$$

If the profit at left side can be written as a function dependent on price at right side, we can come up with the ideal pattern mining for an optimal price. Doing so with two substitutions: *CA* for $BE^{\star}UM$ and $P-CM$ for *UM, Profit* can be alternatively expressed as:

$$Profit = [RP_s(P - CM_s) - CA_s] + [RP_{ltv}(P - CM_{ltv}) - CA_{ltv}] \ldots \qquad (3)$$

Assume the linearity for demand-price relationship holds true at an acceptable confidence level. Mathematically,

$$RP = a + bP \ldots \qquad (4)$$

where *a* refers to intercept and *b* to slope. Combing (4) with (3), the formula for *Profit* versus *P* can be rewritten as a standard quadratic function:

$$\boldsymbol{Profit} = (b_s + b_{ltv})\boldsymbol{P^2} - [(b_s + b_{ltv})CM - (a_s + a_{ltv})]\boldsymbol{P} - [(a_s - a_{ltv})CM + (CA_s + CA_{ltv})] \ldots \qquad (5)$$

As bolded in this pricing model, the final *Profit* is merely related to *P* in conjunction with the other constants. Presumably, *CM* remains unchanged over time whereas *CA* is irrelative to *P* (Banker and Potter, 1993). Since slope *b* is negative because of the inverse correlation between *RP* and *P*, this parabolic curve has an absolute maximum of *Profit* at an optimal *P*, denoted as P_o (Trivieri, 1996). Differentiate *Profit* with respect to *P* in equation (5),

$$\frac{d\,Profit}{dP} = 2(b_s + b_{ltv})P - [(b_s + b_{ltv})CM - (a_s + a_{ltv})]$$

In the above, $d\,Profit/dP$ represents the gradient of a tangent line. Let this differentiation be zero, where a turning point is hereby solved at P_o.

$$P = P_o = \frac{1}{2}\left(CM - \frac{a_s + a_{ltv}}{b_s + b_{ltv}}\right) \ldots \qquad (6)$$

where P_o is an optimal price to maximize an overall *Profit* across a lifetime interval. Taking a closer look at formula above, the pricing model over time can be flexibly applied into either up-front stage by ignoring *ltv* impacts, or follow-up stage regardless of *s* ingredients. As shown in equation (6), however, long-term price (P_o) does not obey the same rule as we did for calculating an overall *Profit* through equation (1). Now plugging P_o, together with the other given constants, into equation (3), a maximal profit is consequently obtained.

According to equation (6), the underling principle for solving optimal price lies on the predictive parameters, *a* and *b*, gleaned from either an initial price-response experiment or a cumulated retention pattern. Although our rigorous pricing model ends up with the plain formulas, it would be more beneficial to have optimal simulations with which marketers are able to respond to pricing dynamics in a prompt and flexible way. The remainder of this article will exemplify a pricing case, where 'what-if' analysis in conjunction with graphic solutions will be presented.

AUTOMATIC FORMATION

'What-if' method examines what output should be if input is altered. This causality, if systematically structured in tableau formation, provides a plenty of flexibility on which marketers can timely monitor how profit is influenced by price along with contextual factors. With a couple rounds of scenario simulation, an optimal price can be readily locked or amended to cope with pricing dynamics. This automatic formation provides a descriptive and operational matrix that conspicuously alleviates the traditional pricing complexity. Nevertheless, a well-designed system is a paramount prerequisite, as detailed below:

Phase I: Case basics

A marketing initiative begins with 10 000 prospects statistically sampled to assure significant findings. Presumably, an advertisement for direct mail campaigns costs US$0.85 per mailing, including its creative design, printing, letter-shop, postage and other expenses related to sales promotion. Thus, *CA* is totalized as $8500 (10 000*$0.85), whereas *CM* is equal to $30 in this example.

Typically, the fixed costs such as management, facility, R&D, and so on, are not accounted during analytic proceeding in most circumstances (Balakrishnan and Sivaramakrishnan, 2002). In fact, marketers are more interested in evaluating the campaign effectiveness by using return on investment, that is, ROI (Robinson, 2003). From this point of view, variable costs are purposely broken down into two parts: *CA* and *CM*, where the former is adopted to gauge ROI and the latter is irrelative to promotion but, instead, tied to merchandise being sold. The separation on cost is meaningful for practitioners when viewing outcomes from a set of different angles.

Phase II: Price experiment

Price experiment geared with statistical sampling rules can discover how customers react to changing price cues, which helps exploiting the relationship between response (*RP%*) and price (*P*). According to equation (5), *Profit* has to be solely determined as the function of *P*. This is the starting point to strive for our pricing optimality. Compared with a spot survey and/or inferred projection pertaining to secondary or syndicated data sources, price-response experiment gets hold of the real-marketplace information that truthfully reflects purchasing attitudes toward price differentials (Mohn, 1995).

As illustrated in Table 1, price at $55, $65 or $75 yields the response of 9.13, 7.15 or 5.42 per cent, respectively. Using common tools such as MS/Excel, a linear regression of *Reps%* versus *P* is found with a strong correlation ($R^2 = 0.998$). In turn, parameters are displayed in Table 2, namely, intercept (a_s) = 0.1929 and slope (b_s) = −0.0019. The negative sign of slope just coincides with a classic inversion between price and demand.

Table 1: Find an optimal price ($62.30) that maximizes overall profit ($51 705)

Terms and formulas		*Projection*		*Experiment*			*Projection*		*Optimal*
Acquisition	*P* (by setting)	35.00	45.00	55.00	65.00	75.00	85.00	100.00	62.30
	RP% (actual or predicted)	12.8%	10.9%	9.13%	7.15%	5.42%	3.5%	0.7%	7.7%
	UM (*P-CM*)	$5	$15	$25	$35	$45	$55	$70	$32
	BE (*TCA/UM*)	1700	567	340	243	189	155	121	263
	RP (*N*RP*%)	1280	1094	913	715	542	352	74	773
	Profit [(*RP-BE*)*UM*]	($2101)	$7915	$14 325	$16 525	$15 890	$10 878	($3314)	$16 481
Retention (LTV)	Cum. Retention Rate	279%	252%	225%	195%	170%	142%	100%	204%
	Future *RP* (*N*RP*%)	3573	2754	2054	1394	921	499	74	1578
	Present *RP* (15% discount)	2834	2184	1629	1106	731	396	59	1252
	Present LTV *RP*% (*PRP/N*)	28.3%	21.8%	16.3%	11.1%	7.3%	4.0%	0.6%	12.5%
	GM (*PRP*UM*)	$17 864	$41 311	$51 356	$48 799	$41 463	$27 453	$5207	$50 985
	GCA (by tracking)	$10 879	$9302	$7761	$6078	$4607	$2995	$630	$6574
	NFV (*GM-GCA*)	$6986	$32 009	$43 596	$42 721	$36 856	$24 458	$4578	$44 411
	NPV (15% discount)	$5541	$25 387	$34 577	$33 883	$29 232	$19 398	$3631	$35 224
Overall	Final Reps (cum.)	4114	3279	2542	1821	1273	748	133	2025
	Final Reps% (cum.)	41.1%	32.8%	25.4%	18.2%	12.7%	7.5%	1.3%	20.3%
	Final Profit (cum.)	$3440	$33 302	$48 902	$50 408	$45 122	$30 277	$317	$51 705
Overhead	Initial Profit (Profit/*N*)	($0.21)	$0.79	$1.43	$1.65	$1.59	$1.09	($0.33)	$1.65
	LTV *NPV* (*NPV/N*)	$0.55	$2.54	$3.46	$3.39	$2.92	$1.94	$0.36	$3.52
	Final *NPV* (Final Profit/*N*)	$0.34	$3.33	$4.89	$5.04	$4.51	$3.03	$0.03	$5.17

Table 2: *RP%* vs. *P*

Initial	a_s	0.1929
	b_s	−0.0019
	RSQ_s	0.998
	Initial P_o	$67.00
LTV	a_{ltv}	0.4075
	b_{ltv}	−0.0045
	RSQ_{ltv}	0.991
	LTV P_o	$60.36
Final	RSQ_l	0.994
	Final P_o	$62.30

Moving toward the 2nd, 3rd and the other follow-ups, a retention rate through multiple campaigns is accumulated into 225, 195 or 170 per cent under each discrete price: $55, $65 or $75. Likewise, as shown in Table 2, a simple relationship across LTV is commensurately identified, where $a_{ltv} = 0.4075$ and $b_{ltv} = -0.0045$.

In our analysis, the initial mailings of 10 000 are constantly used as an invariable base to calculate *Reps%* across overall campaigns, including acquisition and retentions. Therefore, the final *Reps%* can be simply lumped together over time, which affirms a comparison between short-term focus and long-term strategy.

Up to this point, optimal prices at each stage – initial, LTV and final – have been solved through equation (6) and exhibited in Table 2. Marketers can readily capture pricing optimization from short-term to long-term, depending on business objective being established or adjusted. Notice the final P_o falls below the initial P_o because of a compensation of LTV P_o. This is LTV principle in action, where marketers should learn how to bear temporary sacrifice in exchange for overall optimization as a strategic whole (Venkatesan and Kumar, 2004).

Phase III: 'What-if' analysis

Next, we will walk through the pricing procedure in which 'what-if' simulation is introduced to simplify empirical pricing complexity. As noted earlier, an entire process and its solution are discussed at two distinctive stages: initial acquisition and LTV retention.

The price-response model is initially implemented to forecast adjacent responses within a prevailing price interval, saying, from $55 to $75. Be aware that the linear trend between price and response could be increasingly skewed as long as prices move beyond some thresholds. For instance, simple regression becomes less predictive at \$100 than at \$85. This implies that optimal price is conditionally projected within a rationalized range while an amendment is required otherwise.

Unit margin can be readily computed as the difference between price and cost for merchandise or service. If price is \$65, for instance, we have,

$$UM = P - CM = \$\,65 - \$\,30 = \$\,35$$

So do others at distinct price levels. Together with CA (total cost for advertisement) of \$8500 as mentioned before, we now find the benchmark for breakeven:

$$BE = \frac{CA}{UM} = \frac{\$\,8500}{\$\,35} = 243$$

where 243 are the minimum responses (that is, sales volume) to cover expenses on advertisement and merchandise. Since the response (RP) equals the product of $N{\star}RP\%$, 715 (7.15%★10 000) respondents are acquired at \$65, 542 at \$75 and so on. Hence, an initial profit can be computed at price of \$65:

$$(Profit)_s = (RP - BE){\star}UM = (715 - 243){\star}\,\$\,35 = \$\,16525$$

With the same formula, profits at the other prices can be accordingly obtained. Looking at profit concavely shaped along prices, as depicted in Table 1, an optimal price scheme should be first narrowed down to a targeted range from \$55 to \$75. Several trials can asymptotically press on toward an optimal price of \$67, which is the same as a result solved from equation (6). 'What-if' algorithm allows marketers to approach optimum price and pursue maximum profitability in minutes.

Thus far, \$67 is merely an optimal point to maximize front-up profit without any follow-up contributions. Since retention programs most likely dominate an overall profitability, few DM strategies, including optimal pricing, is succeeded in absence of LTV engagement (Jackson, 1989). As shown in Table 2, a long-term optimal price goes to \$62.3 instead of \$67, which will be discussed later.

When moving into the retention stage, there are two critical concerns in regard to empirical LTV proceeding. First, how is data tracked, captured and mined to support LTV analysis; second, can LTV be realized in a simplistic yet reliable way.

The first issue basically relies on LTV-centric data mart migrated from IT functional data warehouse (Yang, 2004), which is out of scope in this research. Instead, responding results are directly pulled in accumulated formation over past 3 years. As depicted in Table 1, retention rate pertaining to \$55, \$65 and \$75 has been respectively amounted as 225, 195 and 170 per cent. This downside trend explains that lower prices are able to arouse responding enthusiasm and likely to carry such a stimulus through the end. In other words, a larger consumer's surplus induced with discount incentives appears sustainable to entice more contingent purchases in a competitive marketing context.

Future responses can be computed with $N{\star}RP_s$, as displayed in Table 1. Another consideration in LTV study is time value of money, where net future value (NFV) earned from today's investment must be discounted to net present value (NPV) for a comparison purpose (Hughes, 2002). Mathematically,

$$NPV = \sum_{i=1}^{n} \frac{NFV_i}{(1+d)^i} \cdots \quad \cdots \qquad (4)$$

where discount rate, d, is selected as 15 per cent in our analysis, referring to a prevailing rate in industry (Wheaton, 1998). We take 3 years for tracking period n, over which total (that is, 100 per cent) LTV net stream is distributed as: 50 per cent for Year 1, 30 per cent for Year 2, and 20 per cent for Year 3. Then, NPV can be further developed as follows:

$$NPV = \frac{50\,\% \times NFV}{(1+15\,\%)^1} + \frac{30\,\% \times NFV}{(1+15\,\%)^2} + \frac{20\,\% \times NFV}{(1+15\,\%)^3}$$

As it can be seen in Table 1, the formula above converts future value into present one, which makes it feasible into algebraically combine forward LTV with present value.

To better understand and describe the optimal pricing equation (3), we need to extend the empirical value-discount principle to response-reduction formulation, as shown below,

$$PRP = \frac{50\,\% \times FRP}{(1+15\,\%)^1} + \frac{30\,\% \times FRP}{(1+15\,\%)^2} + \frac{20\,\% \times FRP}{(1+15\,\%)^3}$$

where *PRP* stands for the present responses, and *FRP* for the future responses. Like the capital discount, the conversion for responses is also indispensable to assert a comparable regime confronting different timelines. As exhibited in equation (3), coefficients such as a_{ltv} and b_{ltv} must be determined under the 'present' condition – the same timeline being applied to a_s and b_s.

As long as the transition from *FRP* to *PRP* is completed, our next step is to acquire present *RP%* for modeling LTV price-response, where a_{ltv} and b_{ltv} are accordingly exploited in Table 2. Keep in mind that any response rate, no matter in a short-term or a long-term, must be constantly benchmarked at the initial prospects ($N = 10\,000$) to assure the computational consistency. In consequence, a customer LTV overhead is simultaneously attained once total profit is divided by the same base (*N*). This methodology differs from the conventional LTV method that is based on initial customers being acquired rather than prospects being promoted.

To this end, we can timely simulate many alternative price scenarios leading to the final maximum profitability. As indicated in the field of 'optimal' in Table 1, a few attempts can quickly arrive at an optimal price of \$62.30, on which a long-term profit is subsequently maximized to \$51 705 in total or \$5.17 overhead. In effect, Table 1 containing those contextual variables suggests a flexible and simple way for optimizing price as a strategic capacity.

GRAPHIC SOLUTION

Two graphs are correspondingly drawn to uncover the modeling mechanism, as well as simulating interrelationship among those key impacts relevant to pricing issue.

Since optimal price is only dependent on the price-response model along with constant *CM*, it is consequential to view each pattern and relative positions between short-term, LTV and long-term response rate. Recall all future responses are intentionally assembled on the present timeline to assess their net contributions (Hughes, 1994). As illustrated in Figure 1, final *Reps%* in terms of *N* is virtually made up with a combination of initial *RP%* and LTV *RP%*, where retention efforts add significant impacts on final outcome (Weber, 1996).

On the other hand, all earnings in the future are converted into *NPV* for comparison. A concave shape between profit and price, as shown in Figure 2, mathematically proves the existence of optimal price that results in maximization on profit. Referring to the Table 2 where optimal prices are precisely computed at different stages, Figure 2 pictures an optimal point shifted from short-term (that is, \$67.00) to long-term (that is, \$62.30) because of the influence of LTV stream (that is, \$60.36). This is what LTV acts as a strategic role, where direct marketers can base the optimal pricing model and adjust it from short-term focus to long-term benefit.

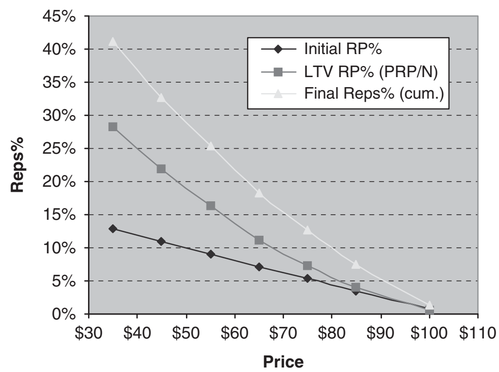

Figure 1: *Reps%* comparison: Initial~LTV~final.

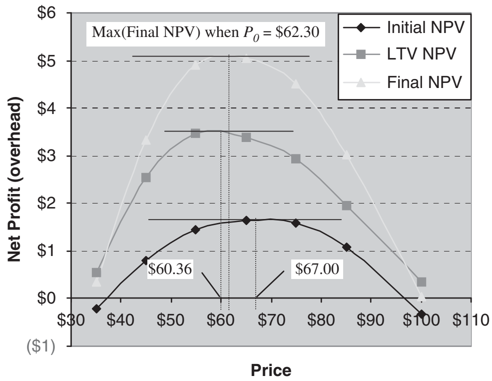

Figure 2: NPV overhead: Initial~LTV~final.

SUMMARY

Literature comes to no argument about importance and recognition of optimal price in any cases. The challenge is how we create a pricing model that appreciably favors to practitioners. Optimal pricing cited in most literatures seems deficient in systematically providing a practical guideline, specifically with respect to a LTV strategic implication. Alternatively, prices are habitually determined by conceptual approaches, brainstorm inputs, or even outright dogma in light of top management's wisdom (Hahn, 2002). As evidenced historically, any plausible claims and opinions without a solid framework often elicit pricing flaws either inevitably devastating profitability or unconsciously missing ample opportunities. It is apparently an emerging task to put forward a convincible solution being counted on to a large extend.

Pricing is complex because of contextual factors influencing price tiers over time. Pricing, in the meanwhile, needs to be simplified for managerial implications. A pricing model with such compromise must be not only fundamentally constructed, but also realistically operated thereafter. In this regard, the author suggests conjoint analyses blended in a rigid algorithm with simulation-based replenishments as well as visual illustrations. Armed with those sophisticated yet practical approaches, direct marketers can dynamically probe into pricing problems without remarkable afflictions as encompassed before.

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